HOLOPHAM: AN AUGMENTED REALITY TRAINING SYSTEM FOR UPPER LIMB MYOELECTRIC PROSTHESIS USERS

by

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Abstract

From hook-shaped prosthetic devices to myoelectric prostheses with increased functional capabilities such as the Modular Prosthetic Limb (MPL), upper limb prostheses have come a long way. However, user acceptance rate does not show a similar increasing trend. Functional use training is incorporated into occupational therapy for myoelectric prosthesis users to bridge this gap. Advancements in technology for virtual and augmented reality enable the application of immersive virtual environments in prosthesis user training. Such training systems have been shown to result in higher user performance and participation in training exercises.

The work presented here introduces the application of augmented reality (AR) in myoelectric prosthesis user training. This was done through the development of HoloPHAM, an AR training tool designed to mimic a real-world training protocol called Prosthetic Hand Assessment Measure (PHAM). This AR system was built for use with the Microsoft HoloLens, thus requiring a motion tracking system that could enable the user to move around freely in a room. The Bluetooth Orientation Tracking System (BOTS) was developed as an inertial measurement unit (IMU)-based wireless motion tracking system for this purpose. Performance of BOTS as a motion tracker was evaluated by comparison with the Microsoft Kinect sensor. Results showed that BOTS out-performed the Kinect sensor as a motion tracking system for our intended application in HoloPHAM. BOTS and the Myo armband were combined to form a human-machine interface (HMI) to control the virtual arm of HoloPHAM, enabling virtual object manipulation. This HMI along with the virtual PHAM set-up makes HoloPHAM a portable AR training environment that can be applied for prosthesis user training or evaluation of new myoelectric control strategies.

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I dedicate this thesis to my parents, Baskar Kothandaraman and Apitha Iyer, whose love and support made all of this possible.

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1. Introduction

Loss of upper limb can have severe physical and psychological impacts on one's life. A variety of methods of rehabilitation therapy are being practiced by the healthcare community to alleviate pain and functional impairment that follows upper extremity amputation. An upper limb prosthesis plays a vital role in adapting to life with an amputation by restoring partial functionality to the patient's residual limb and addressing the cosmetic effect of limb loss. Great advancements have been made in developing technology for such prostheses. However, amputee acceptance rates and feedback on upper limb prostheses do not follow the same trend in growth as emergence of new prosthetic technology. Training to learn methods of prosthetic control can help bridge this gap between development of prosthetic technology and rejection rates of upper limb prostheses. Therefore, rehabilitation often includes training for more effective use of an upper limb prosthesis.

This chapter will highlight some major problems faced by victims of upper limb loss and methods of therapy used to address these problems. It will also cover the role of virtual reality (VR) and augmented reality (AR) in upper limb rehabilitation therapy for amputees, serving as an introduction to the developmental aims that led to this thesis.

1.1. Need for user training in rehabilitation

About 700,000 people in the United States are living with upper limb loss. [43] The alterations in appearance and lifestyle that result from an amputation are the source for many psychosocial [10] and functional challenges.

Neurological conditions are also a consequence of limb loss. These conditions can present themselves as residual limb pain (RLP) and/or perception of the phantom limb. [17] The phantom limb is used to describe the missing portion of the limb that is perceived by the amputee. The presence of phantom limb is felt through painful or touch and pressure-like sensations originating from the missing limb, and perception of voluntary or automatic movements of this limb. Based on the type of sensation felt from the phantom limb, perceptions can be categorized as phantom limb pain (PLP) or phantom sensation (PS). [40] Reilly et. al. studied the EMG patterns produced in the residual limbs of below-elbow amputees who possessed the ability to voluntarily move their phantom limb and an amputee who experienced a frozen phantom limb. The study revealed that attempts to perform different voluntary movements of the active phantom limb produced distinguishable EMG patterns in the residual limb while attempts at different movements produced the same EMG pattern in the residual limb of the amputee with perception of a frozen phantom limb. [38] This increased ability to perform distinguishable EMG patterns for different intended movements because of the presence of an active phantom limb can improve the user's control of a myoelectric prosthesis. These EMG patterns show activations of muscles that are not normally associated with movement of the intended portion of the upper limb in an able-bodied person, thus representing the reorganization in the sensorimotor cortex that is a consequence of amputation. [13], [36] However, the amount of modulation in EMG signals resulting from attempts to move the phantom limb has been positively correlated to intensity of PLP. This increased modulation is a measure of the ability to produce distinguishable EMG patterns for different movements, thus suggesting that PLP might play a positive role in myoelectric control. [13] Increased PLP can also discourage the amputee from attempting to move the phantom limb which reduces an amputee's motivation to use a prosthesis. Currently, rehabilitation therapy for upper extremity amputation is inclusive of methods of PLP and RLP management with the goal of minimizing such negative impacts of pain on functionality and assist the victim in coping with life after limb loss. However, it can also prove beneficial to include plans to maintain and enhance an amputee's natural phantom limb motor control capabilities as this can potentially improve prosthesis user experience through improved myoelectric control.

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The functional ability of the user can be partially restored through body-powered and myoelectric prostheses. [42] A survey was conducted amongst upper limb amputees and limb-deficient persons. The average response to a question on prosthesis wearing time in this survey was "once in a while". [9] In the same survey, 45% of prosthesis users rated their satisfaction performing specific activities as "just satisfied". These activities were mostly daily tasks such as tying shoelaces, peeling vegetables, buttoning shirt sleeves, etc. To summarize, out of 65 respondents, only 28% were satisfied with their functional abilities using a prosthesis. [9] Tremendous advancements in prosthetic technology over the years has increased the functional capabilities of upper limb prostheses. However, a literature review from 2011 showed that myoelectric upper limb prosthesis rejection rates remained at around 30% of prosthesis users for the last 25 years. [3] User feedback analysis has revealed non-intuitive control, insufficient feedback/lack of a closed-loop system and insufficient functionality as three main reasons for prosthesis rejection. [8], [33] While research and development continues to address the problems of insufficient feedback systems and functional capabilities, certain training exercises can be adopted to circumvent the limitations of non-intuitive control and improve prosthesis user functionality. Therefore, inclusion of such training exercises in the rehabilitation program can increase prosthesis acceptance rates.

1.2. Upper limb rehabilitation therapy

Rehabilitation therapy is a consortium of physical and psychological therapy sessions that provide a well-rounded environment for coping with upper limb loss. The therapy sessions that focus on partial to full restoration of lost functional abilities are referred to as occupational therapy. This part of upper extremity rehabilitation for amputees can also involve the introduction of an active prosthesis and training to learn prosthetic control.

Different treatment methods are used at various stages of occupational therapy. Each set of physical exercises or treatment methods is used to address a specific consequence of limb loss, such as PLP, muscle activity in residual limb, setup and use of a prosthesis. The sections below describe the different stages of occupational therapy followed by different methods adopted for physical rehabilitation.

1.2.1. Occupational therapy for prosthesis users

Occupational therapy is a critical part of rehabilitation for those with upper limb amputations, facilitating the performance of activities of daily life (ADLs). It can be divided into four phases. [14]

1.2.1.1. Acute phase

This is the first stage of therapy where the practitioner begins to evaluate the patient and creates a personalized plan to address range of motion, pain management and provide psychological support. [14]

1.2.1.2. Pre-prosthetic training phase

This phase focuses on evaluating the patient's muscle activity (number of available muscles for control, strength and cognitive ability to control) [21] and introducing the him/her to the skills required to perform ADLs as they would with a prosthesis [14]. Virtual evaluation and training systems play an important role in determining the optimal muscle sites on the patient's residual limb. It enables the real-time assessment of muscle signal patterns and provides the patient with an interface to practice with. [21] One such system is that developed for the DynamicArm (Ottobock Healthcare, Duderstadt, Germany). However, this training system does not account for changes in arm position and the requirement of sequential movements to operate a prosthesis which can reduce functional outcome when the patient performs tasks with the prosthesis. Task-based VR training systems can introduce the user to such maneuvers at an early stage allowing them enough practice to adapt to performing tasks when fitted with a prosthesis.

1.2.1.3. Basic prosthetic training phase

Once pre-prosthetic training is complete, the patient begins training for prosthetic control through repetitive drills, performing sequence of movements involved in ADLs. Patients are taught to use the prostheses in the correct manner. Instructions for donning and doffing, methods of control and reducing the loading effects form the main part of this training phase. [14]

1.2.2. Current treatment methods

Each stage of occupational therapy focuses on reducing the impact of a specific problem associated with amputation. Majority of these problems are addressed through physical exercises aimed at strengthening muscles and correcting posture that enable easier adoption of a prosthesis at later stages of therapy. In subsequent sections, these exercises included in occupational therapy are described in more detail.

1.2.2.1. Postural exercises and strengthening

The first stage of treatment starts right after amputation, in the form of correct positioning of the residual limb. Often, patients tend to assume the most comfortable or pain-free position. This may not be the optimal posture and can lead to shortening of residual muscles or stiffening of joints. Therefore, immediate post-amputation treatment includes correction of posture to extend the residual limb as much as possible. Exercises to stretch residual limb musculature are adopted to prevent shortening of the muscles. [44]

The missing limb also causes loss of weight on the amputated side. This can lead to a perception of imbalance that can further lead to poor posture of the torso. Different muscle strengthening exercises are performed in acute phase of occupational therapy to maintain a healthy back posture. Once a prosthesis is worn, the perceived loss of mass is compensated for. [44]

1.2.2.2. Pain Management

The two major sources of pain are RLP and PLP, as discussed earlier. Mirror therapy is a common form of treatment used for PLP management. In this method of treatment, the patient holds the unaffected limb in front of a mirror and positions the residual limb behind the mirror such that the reflection of the unaffected limb superimposes the perceived phantom limb. [37] The patient is instructed to mirror the perceived phantom limb movements with the unaffected limb, as shown in Figure 1. The reflection of the intact limb superimposed over the perceived phantom limb serves as visual feedback in the motor command loop, facilitating voluntary movement of the phantom limb and reducing phantom pain. [29]

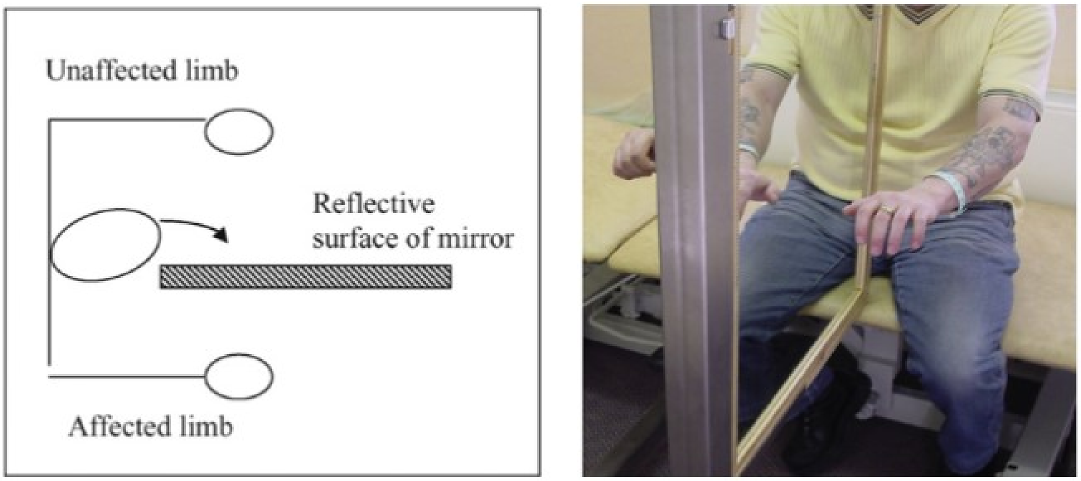

Figure 1. Mirror therapy: Position of mirror for upper limb rehabilitation (left), and visual of patient undergoing therapy (right). [29]

1.2.2.3. Introduction to prosthetic control

Prosthetic control strategies are first introduced in the pre-prosthetic training phase of occupational therapy. In the case of myoelectric prosthesis users, the number and strength of muscles available in the residual limb is used to determine the type of prosthetic control to be implemented – direct or pattern-recognition based. There is a long wait period before an amputee is fitted with a prosthesis due to the need to custom design and fabricate sockets. During this period, the patient is made to practice producing distinguishable muscle activation patterns through prompts of different gripping actions on a screen or by an occupational therapist. Performance feedback is provided in the form of myoelectric signal viewer or movement of a virtual arm on a screen based on the activation patterns produced. [39]

1.2.2.4. Training for ADLs

Achieving a quality decoding performance doing activities of daily life (ADLs) requires multi-DOF movements. However, conventional prosthetic control strategies require performance of sequential one-DOF movements to complete a task. In addition to adopting this non-intuitive control scheme, the postural changes and added weight from wearing a prosthesis will affect pattern recognition-based control. Therefore, the prosthesis training phase of occupation therapy includes repeated training protocols that prompt tasks designed to resemble ADLs. [39] Different performance metrics are determined from many of the standardized training protocols to evaluate functional ability of the patient using a prosthesis. Some standardized protocols that are commonly used to evaluate upper limb functionality have been adopted for this phase of training. These standardized protocols are described in greater detail in the next chapter.

1.3. Virtual reality rehabilitation

VR is a computer-generated portion of the environment that is designed to mimic the real-world. The development of head mounted portable VR visualizers such as Oculus Rift, HTC Vive and Google Cardboard immerse users in virtual environments that can be set up to mimic daily activities. VR has been used in functional recovery training and evaluation systems in lower limb [12], [31] and stroke rehabilitation [27], [41]. More recently, the concept of AR has taken virtual environments one step further by integrating these environments into the real-world by rendering virtual objects through a see-through head-mounted display (HMD) such as the Microsoft HoloLens. From the perspective of upper limb rehabilitation for amputation, such technology enables the development of visual feedback through generation of a virtual limb in place of the missing limb that can be moved and controlled through motion tracking systems such as the Leap Motion or Microsoft Kinect and bio-signal acquisition systems for human-machine interfacing. Such VR environments with overlaying virtual limbs have been adopted as alternatives to mirror therapy for PLP management. [32]

Introduction of real-world training protocols in the pre-prosthetic training phase is limited by the inability to interact with objects in the absence of a prosthesis due to amputation. [30] The development of EMG-controlled virtual upper limb prostheses and training environments can overcome this limitation and is utilized to introduce training into a much earlier stage of rehabilitation, thus increasing practice period for a user.

Many research groups have developed training environments using physics engines [20], [23], [45] with objects that these virtual prostheses [5] or virtual hands [4] can interact with. This has led to the development of task-based VREs that resemble real-world training protocols described above. [4], [22]–[24] Various performance metrics can be incorporated to utilize VREs for evaluation of prosthetic control algorithms. [4], [22]

1.3.1. Pain management through virtual arm and games

Representing visual feedback for the phantom limb during attempts to move have shown to reduce PLP through reorganization in areas of the cortex. [32], [36], [37] This mechanism was used as the basis for development of an AR system that places a virtual limb at the end of the residual limb, as shown in Figure 2. A virtual arm with a pattern-recognition based controller was used to develop three different types of virtual training environments. Each of the environments is described in Figure 2. The effect of training sessions with this system on PLP was evaluated through different measures of pain such as the numeric rate scale of no pain (0) to maximum pain (10), the pain rating index (scale 0 to 75) estimated from McGill Pain Questionnaire and pain frequency on a descriptive scale. Training with the system for 12 months showed a continuous reduction in PLP by all metrics. [32]

1.3.2. Standardized training protocols in VR

Task-based virtual training environments developed with a virtual prosthesis can improve user experience and functionality using a prosthesis. This can lead to an increase in prosthesis acceptance rates as described earlier. Such task-based virtual training environments, with incorporated performance metrics, can also be utilized as thorough evaluation systems for prosthetic control algorithms. Modified Box and Block Test (MBBT) and Southampton Hand Assessment Procedure (SHAP) are two standardized training protocols that have been replicated in virtual environments equipped with a virtual prosthesis to enable object interaction, as shown in Figure 3. [23], [24] User performance in virtual MBBT were similar to average performance in real-world MBBT reported in previous studies. [24] Though virtual MBBT had its deficiencies such as lack of an immersive experience and comparison to its real-world counterpart under identical conditions, this highlights the potential of using virtual training systems as alternatives for their real-world counterparts.

1.3.3. Effectiveness of VR rehabilitation

Many research groups have published on VR environments used in various types of rehabilitation programs for restoration of upper and lower limb functionality. However, there continues to be mixed opinions on the effectiveness of utilizing VR for such applications. Howard et. al. performed a meta-analysis of such published data to determine overall effectiveness of VR rehabilitation. [16] This literature review aimed at answering two main questions – Are VRR programs effective? What are the reasons for the observed result? The selected sources were categorized into motor control, balance, gait or strength based on targeted outcome for rehabilitation.

This analysis revealed that those in VRR programs showed improvements in physical abilities significantly above those of comparison groups. Review of sources attributed the effectiveness of the VRR programs to three factors – increased excitement, increased physical fidelity, increased cognitive fidelity. [16]

Conventional rehabilitation programs, as described earlier, require patients to perform repeated tasks that are prompted with a lack of immediate stimuli or motivational scoring system. Therefore, these programs are perceived as boring leading to reduced motivation for the user. VR is suggested to add excitement to the program through the immersive HMDs and game-like design with scoring systems. This increased excitement and motivation leads to patients enjoying their experience, which is a likely cause for better performance.

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Training exercises of conventional rehabilitation programs often focus on performing practice tasks, such as finger tapping exercises and producing various grip patterns, that do not resemble the complexity of ADLs. The flexibility to generate a variety of custom environments that the user can interact with leads to the development of virtual training environments with increased physical fidelity. These realistic environments prompt realistic practice that could be a potential cause for increased effectiveness of VRR programs.

Practice exercises of conventional rehabilitation programs of restoration of upper limb functionality are usually performed under ideal conditions with minimum external stimuli. However, day-to-day use outside a clinical environment can be accompanied with other such stimuli that can result in larger cognitive demand to perform the same task. VR environments can be designed to provide scenarios with different levels of distraction that demand more attention from the user to perform prompted tasks. Training under such increased cognitive fidelity can lead to better user performance outside the clinical environment, thus explaining the increased effectiveness of VRR.

Figure 2. Motor phantom execution using MR and VR: A. Virtual arm rendered at position indicated by fiducial marker in live video feed from webcam, B. The marker and surface EMG electrodes used for pattern-recognition system, C. Virtual arm used as prompt to show target postures as a rehabilitation task, and D. Racing game given as a task where the car is controlled by pattern-recognition system. [32]

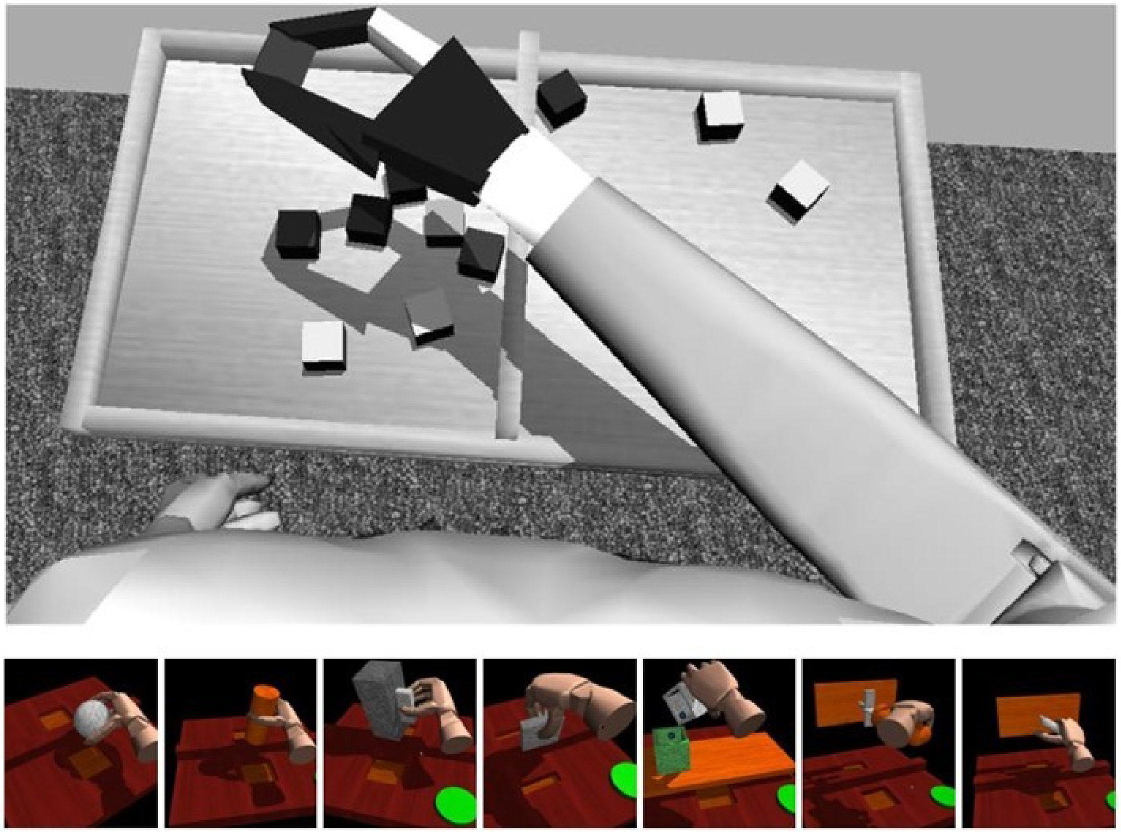


Figure 3. Virtual training environments with standardized protocols: MBBT (top panel) [24] and SHAP (bottom panel) [23].

2. Standardized Training Protocols

Physical training provided for patients through upper extremity rehabilitation programs is aimed at restoring the user's ability to perform ADLs with the affected limb. Periodic evaluation of upper limb functionality through performance of different tasks is utilized to monitor the effectiveness of the implemented training program and make modifications to future sessions of the program. Standardized training protocols have been designed to enable training through various tasks and simultaneous evaluation of targeted limb functionality during task performance. Such protocols play the role of outcome measures that reflect user performance and are widely used in upper extremity rehabilitation in stroke patients. These outcome measures have also been applied to amputees for training and evaluation of their functionality with a prosthesis. Standardized training protocols also play an essential role in evaluation of new prosthetic control methods developed by research groups.

Different factors such as extent of paralysis for stroke patients or the number and strength of residual muscles for amputees raise the necessity to plan different training sessions that cater to each patient's condition and requirements. Therefore, the application of training protocols designed for stroke rehabilitation in upper limb amputee rehabilitation might not be optimal for user training in prosthesis control. Therefore, the goal of this project was to develop a training protocol, specifically designed for upper limb amputee rehabilitation, in a virtual environment that can be used to effectively evaluate and improve user functionality with a myoelectric prosthesis. In order to achieve this goal, it is important to understand the needs of the victims of limb loss and develop training protocols accordingly. In this chapter, certain aspects of training protocols are highlighted, giving the reader some insight into features that make a training protocol effective for rehabilitation of upper limb amputees. This chapter also includes a review of current standardized protocols applied in rehabilitation of upper limb amputees, keeping in mind the preferred features for training protocols.

2.1. Features of an effective training protocol

The final outcome of a training protocol must be improved user satisfaction when performing ADLs with an upper limb prosthesis. There are a number of factors that can influence user satisfaction such as the ability to control grip actions over a larger range of motion, discomfort felt by the user due to strenuous compensatory movements and postures to complete the intended task, and painful sensations due to PLP, loading effects of the prosthesis or ill-fitting socket. These factors can be monitored and addressed through the incorporation of certain features into the training protocol designed. This section will describe three such features identified as contributing factors to an effective training protocol for upper extremity rehabilitation of amputees.

2.1.1. Tasks that mimic ADLs

Some of the training protocols that are used during the pre-prosthetic phase of occupational therapy or in prosthetic control system evaluation involve tasks largely focused on control of different grips in a myoelectric prosthesis without any significant changes in arm position or movement of intact joints in the residual limb. [34], [39] While such protocols serve well as an introduction to prosthetic control techniques, they do not account for many influential factors present during performance of ADLs such as changes in arm position, electrode displacement and compensatory movements performed by the user to complete a task. This led to the adoption of additional training protocols during the prosthesis training phase that involve tasks requiring movement of the residual limb in addition to myoelectric control of the prosthesis grips. These training exercises included using the myoelectric prosthesis to perform activities that mimic ADLs such as zipping up a jacket, using a wallet, and picking up objects of different shapes and inserting them into the appropriate slots in a board. [39] Adoption of these training exercises improve the functional use of the prosthesis. Protocols

STANDARD PROTOCOLS such as SHAP, MBBT and RCRT are standardized evaluation systems that involve tasks that incorporate changes in arm position. These protocols have been increasingly adopted in evaluating user functionality using a myoelectric prosthesis and new myoelectric control strategies in a clinical environment. Therefore, the incorporation of tasks that closely resemble ADLs are preferred to tasks that focus only on myoelectric control training through performance of different grips.

2.1.2. Performance metrics with maximum information

Performance metrics enable occupational therapists to keep track of progress in training and modify the plan to suit each patient's abilities, thus keeping him/her on an optimum training plan. Current performance metrics such as completion rate and completion times only provide information on whether or not a user can complete the prompted task. However, this is a very binary approach to evaluation and does not reflect the level of difficulty faced by the user to complete the task.

A study applied Fitts' law to 3D target acquisition tasks performed using gesture-based computer interactions, supporting the use of Fitts' law performance metrics for such tasks. [6] Therefore, provision to record the path in which an object was moved during a task can prove useful as it can provide information on the efficiency with which reach-grasp-release tasks were performed through estimation of path efficiency, throughput and overshoot [7]. The inclusion of a motion tracking system in the training protocol enables the incorporation of arm movement analysis in the evaluation of user performance. This information can reveal essential factors such as compensatory movements, indicative of potential discomfort from loading effects of prosthesis or ill-posture, that might contribute to lower performance. This can lead to earlier implementation of correctional exercises to address these issues. [18] Adding a pain index to the user interface that he/she can use to indicate level of pain felt during a training session can also provide information on the need to alter the training plan.

Therefore, performance metrics must be chosen such that they provide maximum amount of information on the effectiveness of the training drill on user performance with the upper limb prosthesis or online performance of a prosthetic control algorithm.

2.1.3. Motivational factors to encourage repetition

Conventional rehabilitation programs often require the patient to perform many repetitions of the same task with little or no immediate feedback as to how they are performing. This can cause patients to lose their motivation to continue training, leading to lower performance. [16]

Many research groups have utilized a game-based approach to encourage the user to perform repetitive tasks well. [11], [32], [35] Such game-based approaches to prosthetic control training were received well by amputees and provided a level of encouragement that led to improved performance. The development of immersive VR and AR training environments are also believed to play a role as motivational factors in user training. [16] Therefore, the inclusion of features such scoring systems or use of game-based VR/AR training systems can motivate prosthesis users to train frequently and try their best to perform all repetitive tasks well.

2.2. Current standardized protocols

There are standardized training procedures that have been developed for the prosthetic training phase of occupational therapy. Generally, these are tasks that involve movement of objects of various sizes in a manner that mimic sequences of movements that are required to perform ADLs. Users are asked to perform these drills repeatedly until performed consistently at 95% to 100% accuracy. [21] Different performance metrics are recorded for different types of protocols to score the user on his/her performance as shown in Table 1. [15], [19], [26]

Training Protocol	**Performance metrics**
MODIFIED BBT	Number of blocks moved to other side in 1 min
RCRT	Time taken to move each pin to target location
SHAP	Time taken to complete each task

STANDARD PROTOCOLS

Table 1. Performance metrics of each real-world training protocol.

2.2.1. Modified Box and Blocks Test

This is a modification of the traditional box and block test developed by Mathiowetz, et. al [28]. The test is set-up by arranging 16 blocks in a box on one side of the divider, as shown in Figure 4. The blocks are arranged in this manner to enable comparison of multiple trials. For each block, the user must grasp the block using the appropriate grip and move it over the divider, to the other side of the box. The user must stand while performing the task and start with the block in the lower inner corner, continue across the row and then proceed to the next row. The goal is to move the maximum number of block possible in 60 seconds. If the user moves all 16 blocks within this time period, the time taken to move all the blocks is noted. Motion capture during each trial can also be used to obtain more information on user performance. [15] Quantitative analysis of motion can enable the addition of parameters such as path efficiency and throughput based on 3D Fitts' Law [7] which can be used for evaluation of prosthetic control.

Though this training protocol prompts tasks that requirement changes in arm position to drop the blocks from one box to the other, the range of motion is still limited and does not resemble the active space involved in ADLs. Therefore, use of other standardized protocols with tasks prompted over a larger active space are preferred to MBBT.

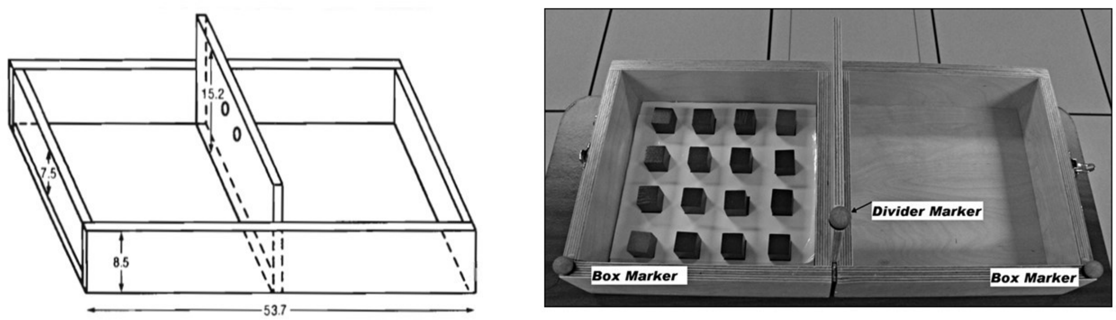


Figure 4. Modified BBT: Dimensions of box used for the test [28] (left), and arrangement of blocks for the test [15] (right).

2.2.2. Southampton Hand Assessment Procedure

This training procedure is unique as it incorporates ADLs and the use of objects of various shapes and sizes. The task can be divided into two categories – abstract objects and ADLs. [26]

Abstract object tasks are similar to the box and block test. Each object can be grasped by performing a specific grip and must be moved from one slot to the other in the form board, shown in Figure 5A. Two objects are used for each shape, one light-weight and the other heavy, to account for loading effects. The user presses the timer button and then starts the task. Similarly, on completion, the user presses the button again to stop the time. Time taken to complete each task is recorded. [46]

The ADLs for SHAP are picking up coins, unbuttoning a buttoned piece of cloth, simulating food cutting, turning a page, twisting open a jar, pouring from a glass jug, pouring from a carton, lifting a heavy object, lifting a light object, lifting a tray, rotating a key, rotating a screw, zipping/unzipping and rotating a door handle. Certain tasks are not used for the test depending on the user's ability to perform the task. Just like abstract object tasks, the time taken to complete each activity is recorded through the timer. [46] As shown in Figure 5, this robust training procedure is packaged into a small portable system.

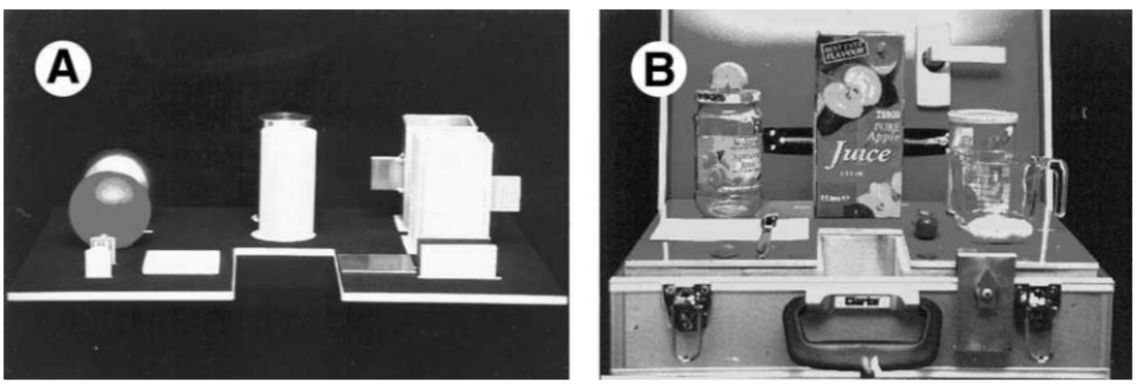


Figure 5. SHAP: A. Set-up for abstract object tasks, B. Set-up for SHAP ADLs. [26]

2.2.3. Refined Clothespin Relocation Test

For this test, the original Rolyan graded pinch exerciser is placed on the edge of the table. As shown in Figure 6, three clothespins are arranged on the middle horizontal rod with equal spacing and at 45° angles upward. The goal is to move each pin from the horizontal rod to a specific position on the vertical rod and vice versa. The user must start the timer when ready to move all three pins to or from the horizontal bar and stop the timer when the he/she is done moving all pins. The test administrator must be ready to place a new pin in the start position in case the user drops a pin. A specific target location is assigned for each pin to compare performance metrics of different trials. Motion tracking also provides information on different compensatory movements performed to complete the task. [19]

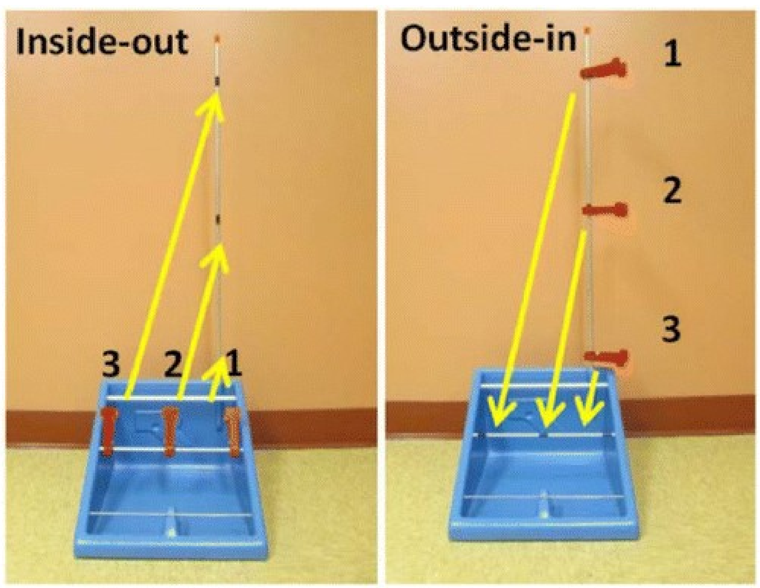


Figure 6. Set-up for RCRT. [19]

2.3. Prosthetic Hand Assessment Measure

ADLs involve a combination of multi-DOF movements over a larger active space and different grips to manipulate various objects. Prosthesis users must perform these activities through sequential movements. Therefore, assessment protocols that incorporate more multi-DOF activities and a larger active space can serve as better outcome measures for prosthesis users. This led to the development of Prosthetic Hand Assessment Measure (PHAM) at the Neuroengineering and Biomedical Instrumentation Lab at Johns Hopkins University. PHAM is a training protocol for upper limb amputees that was designed as an at-work or in-home assessment system. It includes many of the features defined for a good outcome measure. [2], [18] The following sections will describe this training protocol in detail.

2.3.1. Components and set-up

The frame required for PHAM is a 2 X 2 windowpane structure made from 1.5” PVC pipes. The six horizontal and six vertical segments resulting from the windowpane design of the structure serve as possible locations for objects or targets based on the prompted task. Each segment is fit with an LED strip and a holder for the objects as shown in Figure 7.

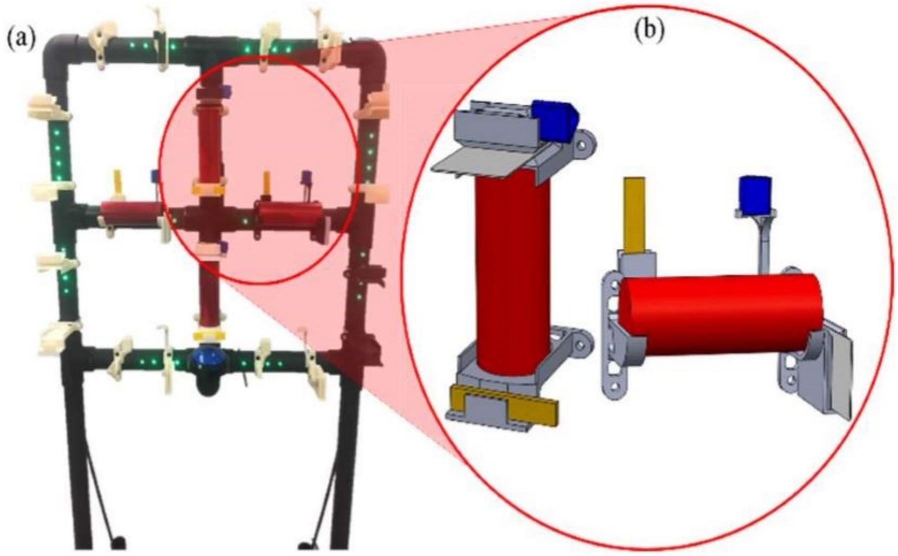


Figure 7. Set-up for PHAM: a. Image of complete PHAM frame and object holders, and b. Image highlighting the difference in design of object holders for horizontal and vertical objects. [18]

Each object holder can hold four geometric primitives, each corresponding to a specific grip for manipulation as shown in Table 2. The holders for horizontal and vertical segments slightly differ in their design to reduce the chances of unwanted collisions with the hand during task completions.

Primitive	**Grip**
Cylinder	Power
Prism	Tripod
Block	Pinch
Card	Key

Table 2. Geometric primitives used in PHAM.

A button is also included in the frame to enable user-driven timer control. Pressing the button starts/stops a timer that is used to determine completion time for each manipulation.

The PHAM protocol is controlled by a GUI designed using Python 3.5. The assessor must enter parameters such as body segment lengths and task timeout, and select a protocol that determines the order and way in which objects are to be manipulated during the experiment.

2.3.2. Tasks

The PHAM requires grasping and movement of objects to different target locations in the frame. Each prompted object manipulation is called a case and a set of four cases is referred to as a trial. Three different types of protocols are supported by the GUI – preset, random, and custom. The preset protocol divides the segments into two categories, as shown in Figure 8, and the cases prompt movement from these inner segments to perpendicular outer segments. The random protocol consists of cases prompting movements from four random segments to corresponding perpendicular segments. For this project, two custom protocols were designed – 'in-to-out' and 'out-to-in'. The 'in-to-out' protocol prompts the movement of objects from the inner segments to adjacent outer segments chosen at random. The 'out-to-in' protocol prompts the movement of objects from the outer segments to adjacent inner segments.

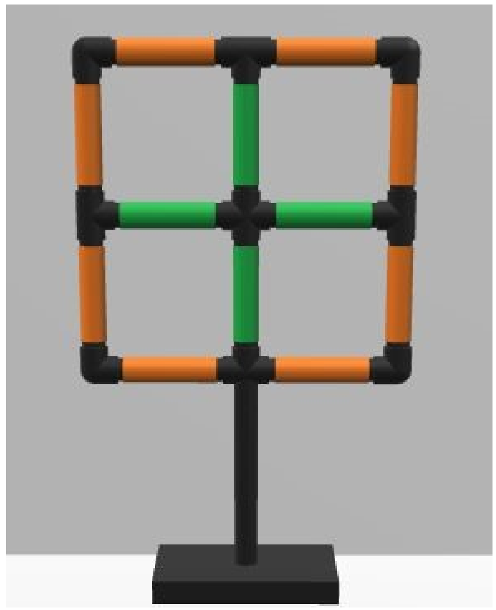


Figure 8. The PHAM frame segments are categorized into inner segments (green), and outer segments (orange).

Once a protocol is selected and all parameters are set in the GUI, all the LED strips flash orange to indicate the start of a trial. Each case is prompted by the lighting up of two segments, one with the objects placed in the holder and the other with an empty holder that serves as the target. The object to be manipulated is indicated by the color of the LEDs, where each color corresponds to a geometric primitive. The object must be moved from one highlighted segment to the other. The user must press the button to start the timer before performing the task. Once the task is completed, the user must press the button again to indicate the end of the case. If the task was completed successfully, the LEDs will turn green followed by lighting up of two segments for the next manipulation. If the task is not completed within the set timeout period, the LEDs will turn red to indicate an incomplete case and then turn off. In this situation, the user must press the button to start the next manipulation. After each trial, the user can rest while the assessor rearranges all the objects for the next trial.

2.3.3. Performance metrics

Completion rate (η), shown in Equation 1, is chosen as one of the metrics as it summarizes functionality with the prosthesis. However, this does not provide information on possible compensatory movements by the user to accommodate for reduced number of DOFs.

$$\eta = \frac{\text{Successful tasks}}{\text{Attempted tasks}} \tag{1}$$

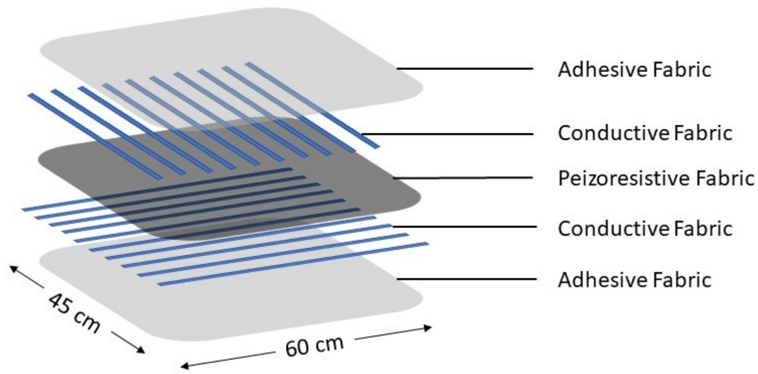


Figure 9. Representation of pressure mat fabrication. Force applied to a section of the peizoresistive grid results in a decrease in resistivity at that location that is seen as a change in voltage. [18]

Kinematics of each task can provide valuable information on such compensatory movements. Data for kinematic analysis is obtained by utilizing two different systems. Orientation of the user's trunk, upper arm, forearm and hand is tracked using a combination of five IMU sensors. Four of the sensors are affixed to the body parts to be tracked while the fifth sensor is placed at the foot of the PHAM frame. Such orientation based motion tracking fails to capture translational movements made while performing tasks. This can also provide information on compensatory movements. Therefore, the user was made to perform all tasks while standing on a pressure mat, as shown in Figure 9. The changes in pressure distribution were used to estimate translation movements by the user. The metrics derived from kinematics are – 3D deviation of the shoulder ($\vec{\delta}_S$), 3D deviation of chest ($\vec{\delta}_C$), and 2D translation displacement ($\vec{\lambda}$). The formula to calculate 3D deviation of a joint X is shown in Equation 2.

$$\overrightarrow{\delta_X} = \sum_{n=1}^{N} \left\| \begin{bmatrix} \varphi_X \\ \theta_X \\ \psi_X \end{bmatrix}_n - \begin{bmatrix} \varphi_X \\ \theta_X \\ \psi_X \end{bmatrix}_{n-1} \right\| \tag{2}$$

where $\overrightarrow{\delta_X}$ represents the 3D deviation of a joint X, and ((n-1), n) represent adjacent time stamps.

A performance score is determined using the metrics specified above. This score, P, is shown in Equation 3. The performance score is inversely proportional to the quality of motion. Therefore, a lower performance score is more desirable.

$$P = \frac{\left\| \overrightarrow{k^T \lambda} \right\|_1 + \left\| \overrightarrow{\delta_C} \right\|_1 + \left\| \overrightarrow{\delta_S} \right\|_1}{\eta} \tag{3}$$

where P is the performance score, and k is a scaling vector proportional to the force mat dimensions.

As mentioned earlier, PHAM is the first training protocol designed specifically for prosthesis user training. The larger active space and resemblance of prompted tasks to ADLs are some of the advantages of PHAM over other standardized training protocols described in the previous section. The performance metric developed for PHAM is inclusive of parameters that reflect compensatory movements performed by the user, thus providing information on user efficiency in task completion, which is essential for satisfactory use of prosthesis in day-to-day activities. Therefore, PHAM was chosen as the reference for the virtual training environment described in this thesis.

2.4. Thesis overview

Training for myoelectric control is a key factor in reducing the probability of prosthesis abandonment by the user. As highlighted in previous sections, current real-world training protocols are limited to the post-prosthesis fitting period due to the lack of a medium of interaction for the user before that. Therefore, once training begins the user must learn the non-intuitive sequential control schema of the myoelectric prosthesis, under conditions of possible increased error rate due to the effects of external factors, such as changing position of the limb and loading effects of the prosthetic arm, on pattern recognition-based classification.

Virtual training systems provide an advantage by enabling interaction between a virtual arm and object without the need for a prosthesis. Therefore, development of such systems can allow for the introduction of myoelectric control training into the pre-prosthetic phase of occupational therapy. Such early adoption of training extends the duration of training period, thus leading to improved user performance. It also provides the opportunity to deploy take-home training systems that might motivate the user to spend more time on training exercises due to the added comfort of training in a home environment.

2.4.1. Development of HoloPHAM

The aim of this thesis is to introduce a new virtual training system called HoloPHAM. This is an AR training environment designed to mimic PHAM. As described in the previous section, PHAM provides training and evaluation for multiple grip patterns over a larger active space, thus making this an effective training protocol. User performance using the PHAM is evaluated using both arm movement patterns and metrics such as completion times and rates, thus providing more information than other outcome measures. These features are the reason PHAM was chosen as the training protocol to virtualize.

HoloPHAM was built for the Microsoft HoloLens as a portable virtual training tool that would eliminate the hassle of set-up and the need for the presence of a practitioner to conduct the training exercises, as is the case with PHAM. In the next chapter, the design and method of development of HoloPHAM will be described in detail.

2.4.2. Evaluation of BOTS

HoloPHAM required the development of a wireless motion tracking system, Bluetooth Orientation Tracking System (BOTS), that would allow the user to move freely while wearing the Microsoft HoloLens. This system was evaluated through a comparative study with Microsoft Kinect to determine its effectiveness as a device for human-machine interfacing to move the virtual prosthetic arm. The design and evaluation of BOTS is described in detail in subsequent chapters.

3. HoloPHAM

The focus of this chapter is to introduce HoloPHAM, an AR environment that has been developed for Microsoft HoloLens. This system renders a virtual PHAM setup and arm in the user's view of the real world. A combination of upper limb motion tracking and a pattern recognition system is used to control the virtual arm and enable interaction with virtual objects on the PHAM frame without the need for a prosthesis. The virtualization of PHAM provides the advantage of automating the entire protocol. In the following sections, I will describe the hardware and software components of the system and environment design.

3.1. Components

Any immersive AR training system requires three essential components – a visualizer, hardware for human-machine interfacing that enables the user to navigate and interact with the virtual world, and a physics engine that is utilized to simulate such interactions. For the HoloPHAM, Microsoft HoloLens was used to render the virtual training environment over the real-world view. The Unity game engine was used to develop the HoloPHAM application and its in-built physics engine was used to simulate physical interactions of the virtual arm with the rest of the virtual environment. A custom-built motion tracking system was used to track upper limb movements while the Myo armband was used to record EMG signals for myoelectric control. Together, this information was used to drive the virtual arm. The following sections describe each of these components in detail and how they were combined to produce the HoloPHAM environment.

3.1.1. Microsoft HoloLens

HoloLens by Microsoft is the first self-contained holographic computer designed as a headset. It renders virtual objects in the form of holograms that overlay the user’s view of the real world, as shown in Figure 10. It also enables interaction between the virtual and real-world objects through spatial mapping and understanding algorithms, thus creating an AR environment. The portability of this headset allows the user to move freely but, imposes the constraint of using wireless systems when motion tracking is required for an application.

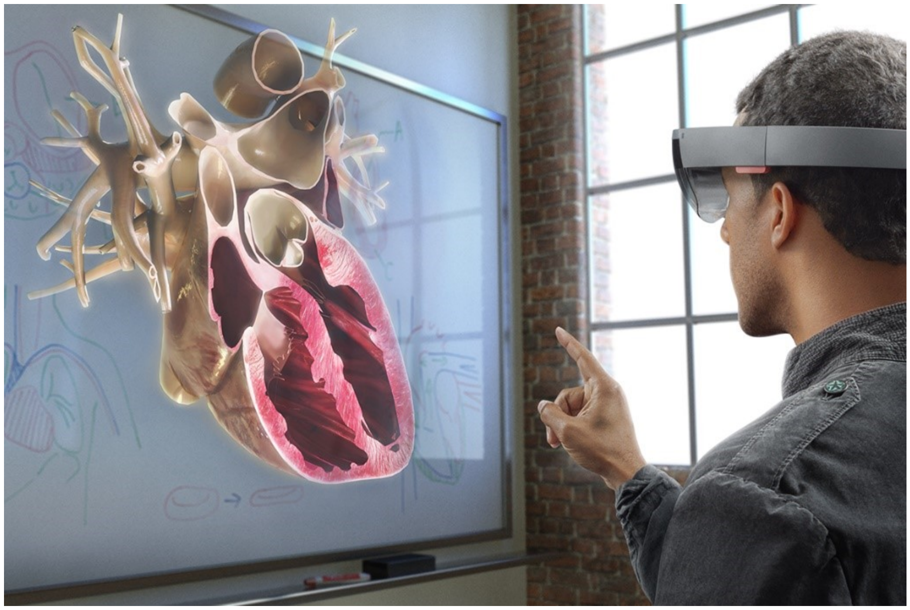


Figure 10. User's perception of the AR environment generated by HoloLens.

3.1.2. Myo armband

The Myo armband was introduced by Thalmic Labs, Inc. as a wearable gesture control and motion control device that can be connected to a PC, laptop or tablet through a Bluetooth adapter. Gesture recognition is achieved through in-built processing of eight-channel EMG signals recorded from medical grade stainless steel electrodes. A nine-axis IMU is also incorporated in the armband to enable motion-based control.

In 2014, the raw EMG data and orientation quaternions were made available to developers to widen the scope of applications of the armband. This data from the armband has been utilized to mimic myoelectric prosthetic control that drives the virtual arm of HoloPHAM. The armband is worn on the user's forearm, closer to the elbow. The 8-channel EMG data is recorded by the armband at a sampling frequency of 200 Hz. This data is used to train an LDA classifier for seven movement patterns of the hand and forearm – hand open, power grip, tripod, index point, forearm pronation and supination. This is then used to determine grips performed by the user and change the virtual arm grip accordingly. LDA was chosen as it is the most popularly used algorithm in pattern recognition-based prosthetic control. In this manner, HoloPHAM is equipped with pattern recognition-based control of the virtual arm.

3.1.3. Bluetooth Orientation Tracking System

The combination of IMU sensors used for upper limb motion tracking in PHAM was designed as a sequential arrangement of the sensors interconnected by data cables. However, as mentioned earlier, use of this motion tracking system with HoloLens proved cumbersome due to limitations imposed by it on the user's freedom to move around. Bluetooth Orientation Tracking System was developed to address this issue.

3.1.3.1. Device description

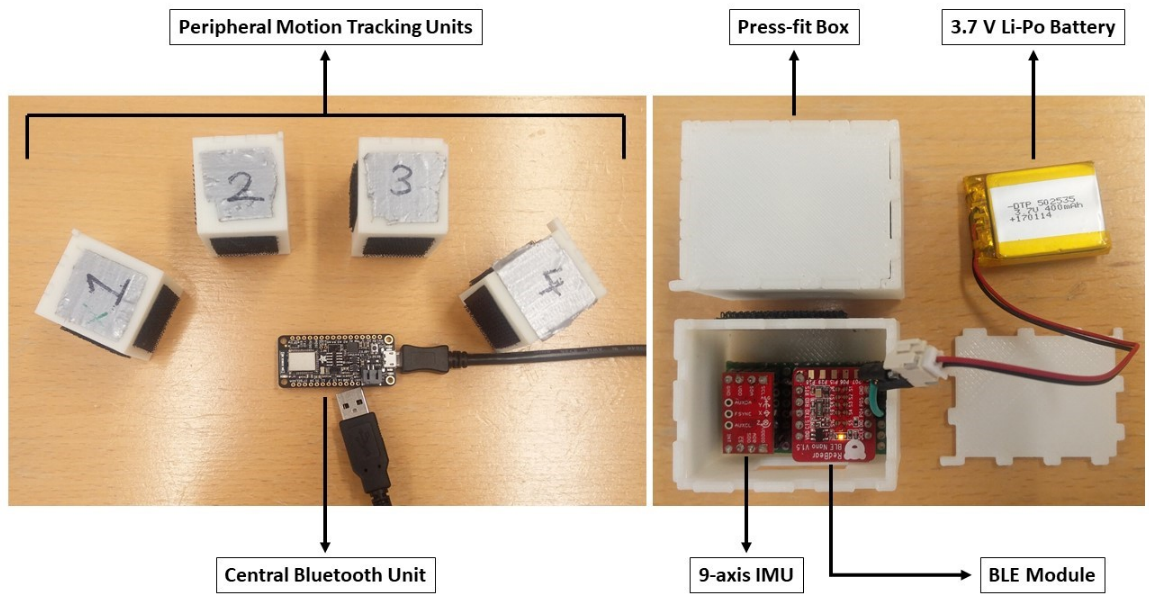


Figure 11. BOTS for HoloPHAM: Picture of Bluetooth motion tracking units and central Bluetooth dongle (left), and components of each motion tracking unit (right).

BOTS is a new motion capture system, consisting of wireless motion tracking units (MTUs) as shown in Figure 11. It was developed by our team for HoloPHAM. Each MTU was constructed using a 9-axis IMU (MPU-9250 Nine-Axis MEMS MotionTracking™ Device, InvenSense, Inc.) and a Bluetooth 4.1 Low Energy (BLE) module (RedBear BLE Nano). The power supply for each unit is provided by a 3.7 V Li-Po Battery creating a self-contained wireless orientation sensor. Every MTU communicates with a central Bluetooth module that is connected to a computer through the USB port. The orientation data from all connected sensors are read through serial communication with the computer.

To capture upper limb movements for this application, three MTUs are fixed to the chest, upper arm and forearm on the side of the body that is to be tracked while a fourth is fixed beside the PC or laptop to generate a reference frame. Orientation data from each MTU are received in the form of a unit quaternion. The tracked orientations of the user's chest and arm are used to generate joint orientations and positions that drive the corresponding parts of the virtual arm in HoloPHAM.

3.1.3.2. Estimating joint positions and orientations

In order to understand the method used to determine joint orientations and positions, I will introduce nomenclature that has been used in equations throughout this section. The MTUs are numbered as shown in Figure 12. $q_{MTU}{}^{n}$ represents the quaternion read from the n^{th} MTU. The orientation of each MTU relative to that of the previous MTU in the sequence 1-4, as shown in Figure 12, is represented as quaternion, q, which is estimated using Equation 4.

$$q^{n} = \left(q_{MTU}{}^{n}\right)^{*} q_{MTU}{}^{n+1} \qquad (4)$$

where q^n is the quaternion representing orientation of $(n+1)^{th}$ sensor relative to that of n^{th} sensor.

Fixation of MTU on the body parts can lead to misalignment between joint axes and IMU axes orientations. Therefore, translating the MTU orientation data into joint positions and orientations requires a calibration step that is used to account for such misalignments. A calibration pose, as shown in Figure 12, is used to determine the offset value (q_{off}) for each MTU by comparing relative orientation of the MTU to the quaternion expected for that unit from the pose, as shown in Equation 5.

$$q_{off}^{n} = (q^{n})^{*} \tag{5}$$

where q_{off}^{n} is the offset value estimated using quaternion representation of orientation of $(n+1)^{th}$ sensor with respect to n^{th} sensor.

This offset is then used to correct the quaternions, as shown in Equation 6, eliminating misalignment with the bone.

$$q_{c}^{n} = q_{off}^{n} q^{n} \tag{6}$$

where q_{c}^{n} is the calibrated quaternion for relative orientation $(n+1)^{th}$ sensor with respect to n^{th} sensor.

The goal is to map the orientation data from MTUs affixed on the arm in use to corresponding parts of an avatar designed in Unity environment. The requires a transformation of the calibrated quaternions from the right-handed coordinate system of the 9-axis IMU to the left-handed coordinate system of the Unity game engine. This set of transformed quaternions (q_c') are computed from the calibrated quaternions based on the mapping scheme shown in Figure 12, as shown in Equation 7.

$$q_c^{n'} = (w, -y, z, -x) \tag{7}$$

where $q_c^{n'}$ is the quaternion obtained by transformation of calibrated quaternion, $q_c^{n} = (w, x, y, z)$, to Unity coordinate system.

These transformed quaternions (q_c') are used to determine joint positions and orientations. The three joints whose positions and orientations are reconstructed in the HoloPHAM environment are the back (B), shoulder (S) and elbow (E). Each joint orientation is represented as the absolute orientation quaternion q_B, q_S or q_E respectively, while the position of each joint is represented as vector $\overrightarrow{v_B}$, $\overrightarrow{v_S}$ or $\overrightarrow{v_E}$ respectively.

Joint orientations can be correlated directly to MTU orientation data as shown in Equation 8.

$$q_J = q_c^{'n} \tag{8}$$

where q is orientation quaternion, J is joint B, S or E, and n is corresponding MTU number 1-3 respectively.

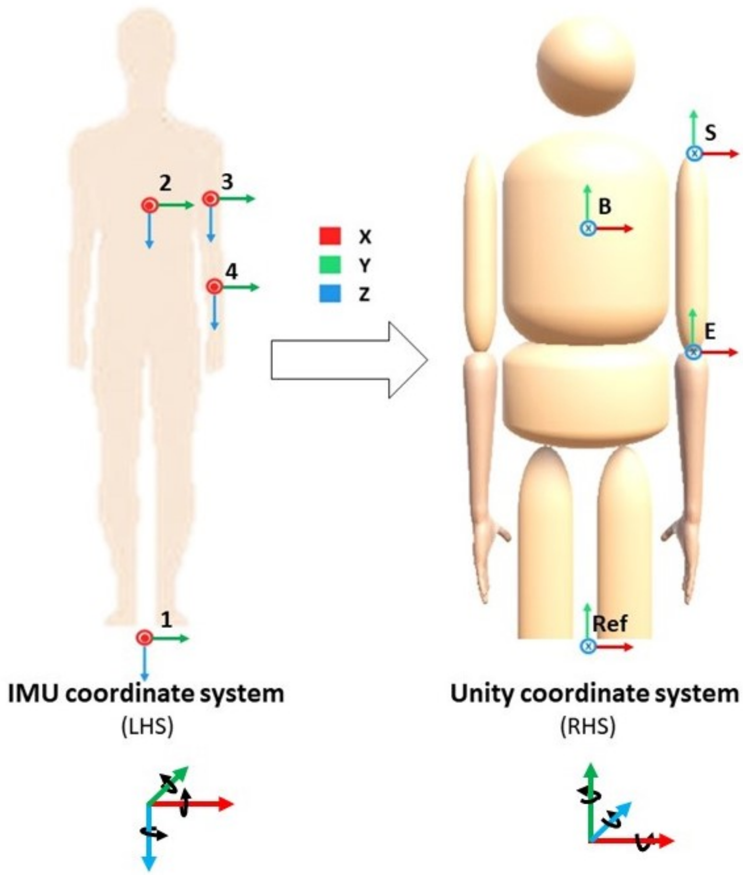


Figure 12. Transformation of orientation data from IMU-based motion tracking system to avatar joint orientations and positions in Unity game engine.

Estimating joint positions requires knowledge of the lengths of corresponding body parts. As HoloPHAM was built in Unity, the length of the three segments, as shown in Figure 13, are given in meters as input to the system and represented in the form of vectors $\overrightarrow{L_{HB}}$, $\overrightarrow{L_{BS}}$ and $\overrightarrow{L_{SE}}$ based on the ideal segment orientation in calibration pose. The joint orientation and length of body segment is used to estimate joint positions using Equation 9a-c.

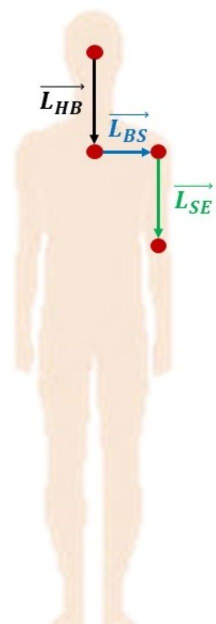


Figure 13. Length of body segments to be entered in HoloPHAM prior to start of training.

$$\overrightarrow{v_B} = \overrightarrow{v_H} + \overrightarrow{L_{HB}} \tag{9a}$$

$$\overrightarrow{v_S} = \overrightarrow{v_B} + q_B\overrightarrow{L_{BS}}(q_B)^* \tag{9b}$$

$$\overrightarrow{v_E} = \overrightarrow{v_S} + (q_S q_B)\overrightarrow{L_{SE}}(q_S q_B)^* \tag{9c}$$

where joint positions are determined using length vectors of body segments and joint orientations [1], and $\overrightarrow{v_H}$ is the position of Microsoft HoloLens tracked in HoloPHAM.

Applying BOTS towards a human-machine interface that drives the virtual arm of HoloPHAM requires good performance of the system in upper limb motion tracking. This was evaluated by comparing its performance with that of Microsoft Kinect, which is described in detail in the next chapter.

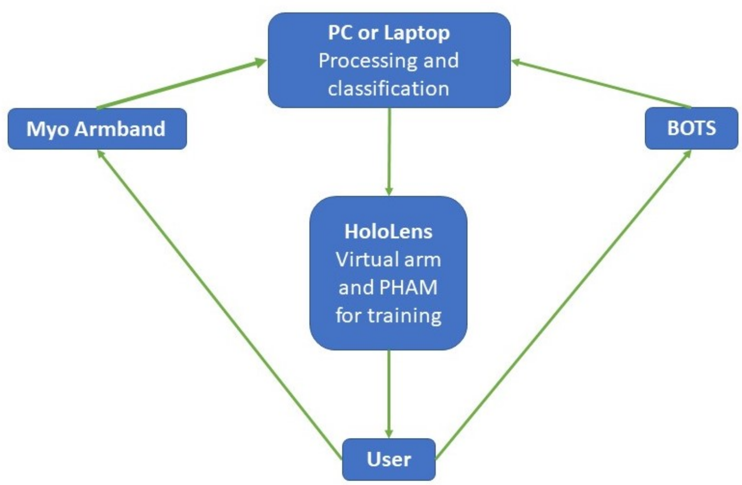


Figure 14. Schematic representation HoloPHAM highlighting to role of each hardware component.

3.2. Design

Unity is a 3D game engine incorporated with the PhysX engine that enables the development of object interaction and manipulation capabilities that are needed for this project. It also serves as a platform for HoloLens application development, where the available features of HoloLens such as spatial mapping and understanding can be accessed by incorporating the HoloToolkit package developed by Microsoft. Unity was used to design the virtual PHAM setup and user-controlled arm. A description of these two major components is given below.

3.2.1. PHAM frame and objects

Unity provides access to a number of geometric primitives such as capsules, cubes, planes, spheres and cylinders that can be added to the environment. However, the windowpane structure of the PHAM frame required the design of a custom prefab for Unity. A 3D model of the frame was developed using the Microsoft 3D Builder and added to the Unity environment.

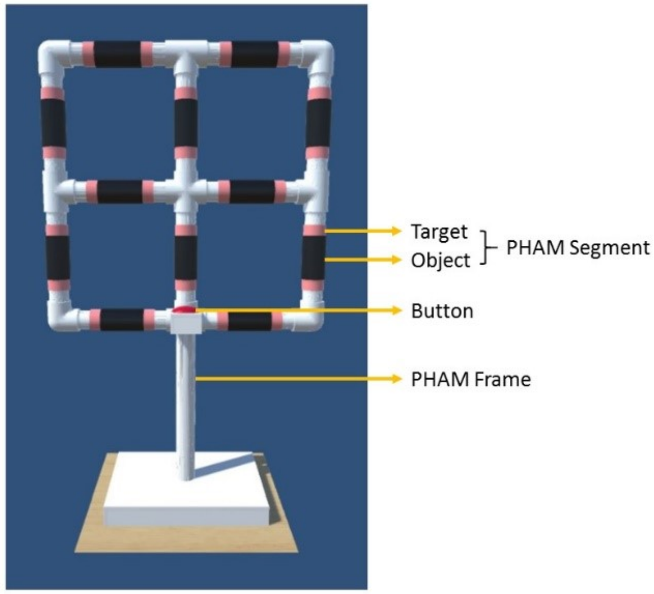


Figure 15. PHAM frame and object set-up in HoloPHAM. The PHAM frame is represented as a white windowpane structure. Each segment of the frame contains the highlighted target area (pink) and the cylindrical object that user can interact with (black).

As this is the first version of HoloPHAM, only cylindrical objects were designed for each virtual segment such that the object could be manipulated by all grip patterns. Future work will include the addition of the other geometric primitives and grip-specific manipulation to HoloPHAM. Each cylindrical object and target space is associated with a collider that is used to simulate object manipulation by the virtual arm. For each trial, an object is highlighted in one segment while the target is highlighted in another segment. The entire set-up design is shown in Figure 15.

3.2.2. Arm

Objects on the PHAM frame can be manipulated using a virtual arm. The arm is rendered as a hologram from a first-person viewpoint. The arm chosen for this application is from the Hand Physics Controller Unity package that utilizes the in-built physics engine to simulate more natural physical interactions with virtual objects.

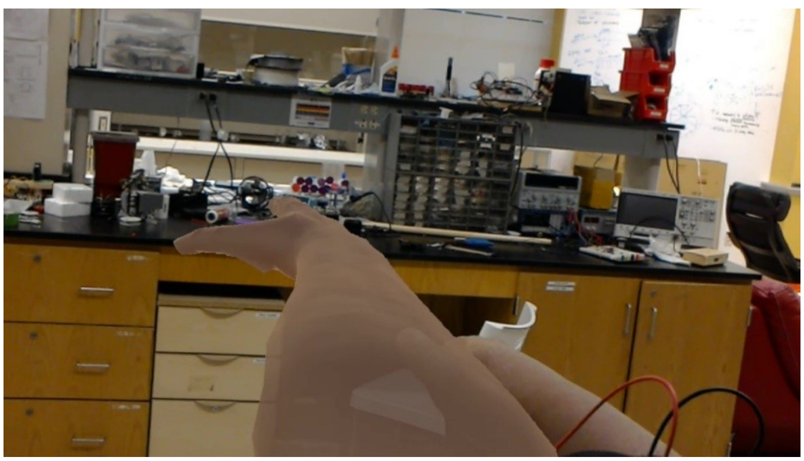


Figure 16. Virtual arm from HoloPHAM driven by BOTS.

The translational movement of the virtual arm is controlled based on the tracked position of the HoloLens along the x-z plane of the Unity coordinate system. This ensures that the virtual arm follows the user around the room. The different joint angles and positions estimated using

BOTS is used to drive the movement of the virtual arm, as shown in Figure 16, while various gripping actions of the virtual hand are performed by interfacing the Hand Physics Controller with class labels generated from online LDA-based classification of 8-channel EMG data acquired from the Myo armband, as shown in Figure 17. This virtual arm control scheme mimics pattern-recognition control scheme implemented in myoelectric upper limb prostheses.

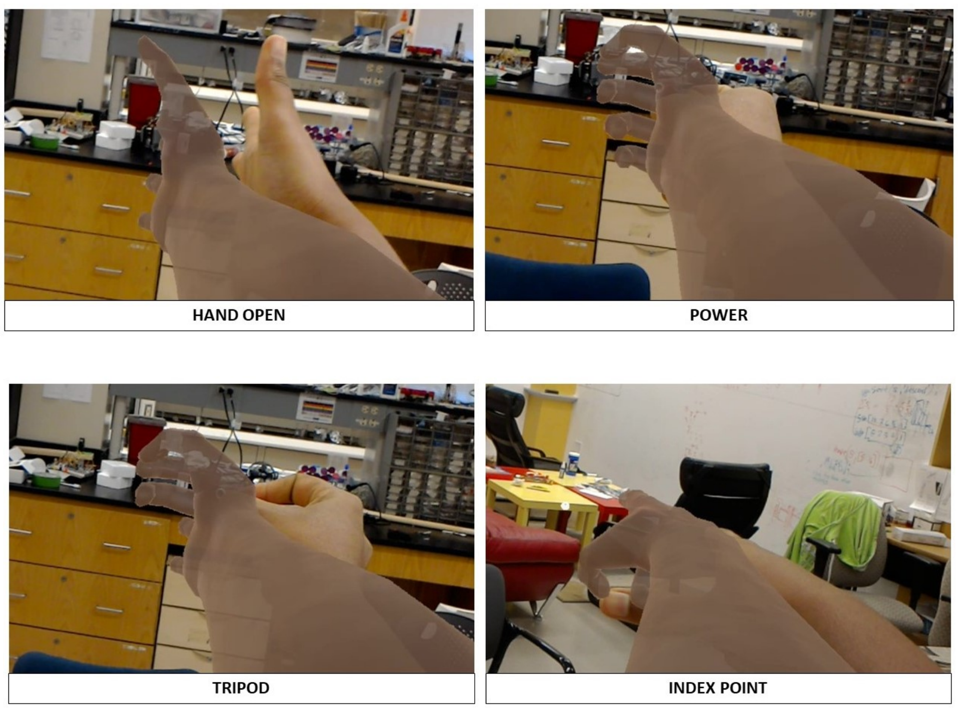


Figure 17. Virtual arm from HoloPHAM simulating different grip patterns through LDA-based classification of EMG signals from the Myo armband.

3.3. Workflow and tasks

This section aims at summarizing the design of the Unity game for the Microsoft HoloLens. It also serves as a user guide that explains different aspects of HoloPHAM and tasks that the user must perform to set-up and use the application.

3.3.1. Organization of game scenes

As is the case with most games designed in Unity, this application also consists of a combination of different scenes, as shown in Figure 18, that are used to generate the final guided training session using virtual PHAM for the user. The next sections will describe the role of each of these scenes and how they produce the final training environment.

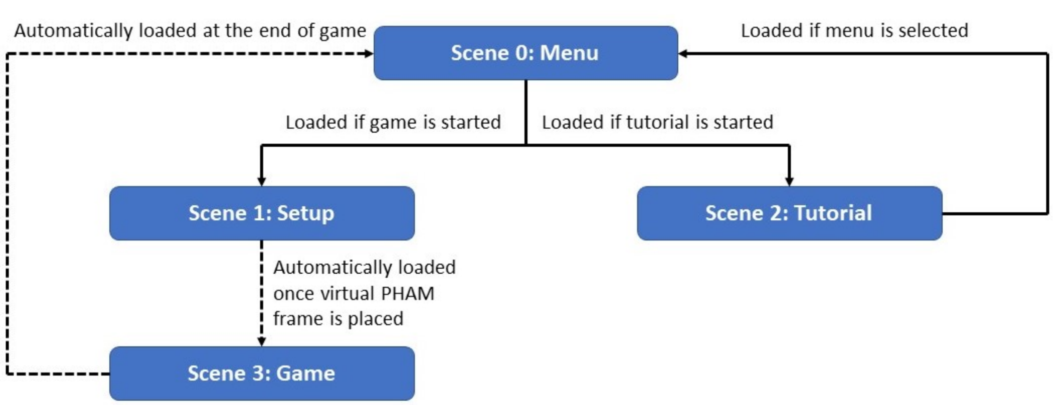


Figure 18. Schematic representing HoloPHAM application workflow and organization of scenes.

3.3.1.1. Menu

As described earlier, the control of the virtual arm and selection of task protocols to be followed requires the need to provide users with the ability to set certain parameters that are used to run the HoloPHAM environment. The purpose of the first scene, the menu, is to fulfill this need through a series of dropdown components that can be used by the user to set-up the system, as shown in Figure 19.

HoloPHAM has been designed as a training system with application in a clinical environment. Therefore, it logs data such as 2D translational movement and 3D joint angles of the limb while the user is performing a task. The 'Subject No.' slot is where the practitioner can select the number assigned to subject. This number is used to name logged data files for easier access in future.

Based on the amount of pain felt by the user or the duration of training already completed during the session, the user may want to adjust the number of repetitions of the set of tasks he/she would like to perform. This can be done by adjusting the 'No. of trials' field. Here, each trial represents a set of four tasks or cases that the user will be prompted to complete. 'Timeout period' is another such metric that can be adjusted by the user based on their level of comfort and efficiency using a prosthesis. This metric defines the amount of time, in seconds, given to the user to complete a single task or case after pressing the button to begin. If the user does not complete the task within this time period, the task is marked as incomplete and the next task is prompted. The fields ‘Object Position’ and ‘Object/Target Orientation’ are used to set the type of task protocol that is prompted. Setting ‘Object Position’ to ‘Inner’ represents the ‘in-to-out’ protocol mentioned in the description of PHAM in the previous chapter, while ‘Outer’ represents the ‘out-to-in’ protocol. The horizontally aligned object and targets in HoloPHAM allow objects to be picked up or placed by either pronation or supination of the hand. Therefore, specifying the type of movement, pronation or supination, sets the HoloPHAM application to look for the corresponding correct orientation of the placed object to determine if the task is completed.

The rest of the variables in the menu are used to set metrics that guide virtual arm control. The field ‘Arm’ is used to set which arm is to be used for training, right or left. The arm selected should match the arm on which the MTUs are affixed. As described earlier, in order to use the MTUs to move the virtual arm, the length of different segments of the user’s body must be entered. The fields ‘Head -> Back’, ‘Back -> Shoulder’ and ‘Shoulder -> Elbow’ are used to set these lengths in inches.

Once all fields have been set, the user can choose to start the training session by clicking on ‘Start Game’ or start a tutorial for HoloPHAM by clicking on ‘Play Tutorial’.

Figure 19. A view of the menu from HoloPHAM through Microsoft HoloLens.

3.3.1.2. Tutorial

The tutorial is included in HoloPHAM to guide the user through the different features of the virtual PHAM set-up that will appear at different stages of the task or case prompted. When the tutorial is played, a virtual PHAM frame appears before the user with a bar for instructions positions above it, as shown in Figure 20. The user can navigate through all the instructions using the ‘Next’ and ‘Previous’ buttons. The ‘Menu’ button can be used to exit the tutorial and return to the menu scene.

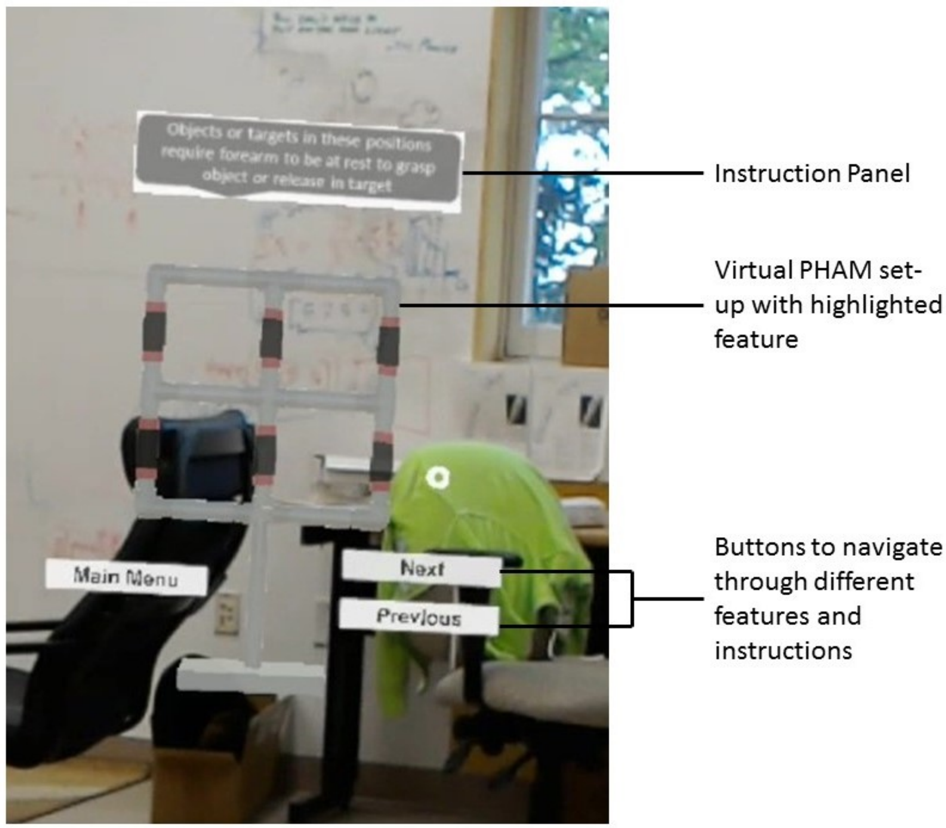


Figure 20. Screenshot of one of the instructions of the tutorial with a description of the virtual components seen.

3.3.1.3. Game

Once the “Start Game” button is clicked, the first scene in a set of two, as shown in Figure 18, is loaded. This scene focuses on the placement of the virtual PHAM frame on the floor of the room with sufficient space around the virtual frame to allow for tasks to be performed. This exploits the Microsoft HoloLens' built-in spatial understanding capability, which can identify basic features of a typical room such as the floor, ceiling, walls and platforms using the input from infrared and depth images from the cameras in the HMD. Once enough space is found, the user is prompted locations, in the form of blue panels on the floor, where the frame can be placed and the frame is placed in the selected location. World anchor on the PHAM frame prevents getting displaced and following the user.

Placement of the virtual frame loads the next scene in the set. This scene activates the virtual arm and its controller. The data to control the arm is received as packets of information through a UDP socket. Once the virtual arm is set-up, the training sessions begin where an object and highlighted target appear rather than the lighting up of segments with LEDs as seen in real-world PHAM.

Once the number of trials set are complete, the data from all trials is saved and the menu is re-opened for the next training session to be set up.

3.3.2. Tasks for user

Many of the scenes described earlier require some tasks to be completed by the user or practitioner in addition to the training tasks. These additional tasks are the selection of metrics to set up the training system and placement of the virtual PHAM frame. The different tasks prompted through the HoloPHAM training session has been summarized in the next few sections.

3.3.2.1. Virtual PHAM set-up

The practitioner or user must set the parameters for HoloPHAM in the menu that renders at the start of the application. The value for each field is set through gaze controlled cursor and 'air-tap' clicks. The next task the user is required to complete is placement of the virtual PHAM frame. This task can be divided into four major steps.

First, the user is prompted to walk around the room, as shown in Figure 21. The room is scanned during this period, while spatial understanding is determining floor space available in the background. When the minimum floor space requirement for the frame is met, the prompt message for the user changes from "Walk around and scan the room" to "When ready, say 'place' or air-tap to finalize your play space", as shown in Figure 22.

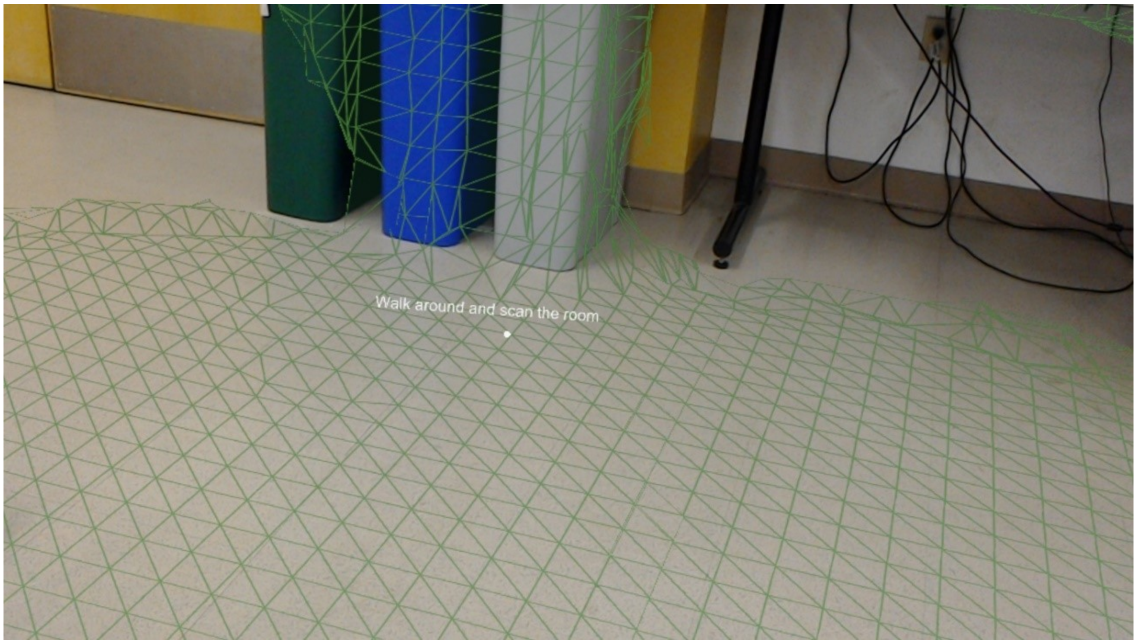


Figure 21. First step in virtual PHAM frame placement.

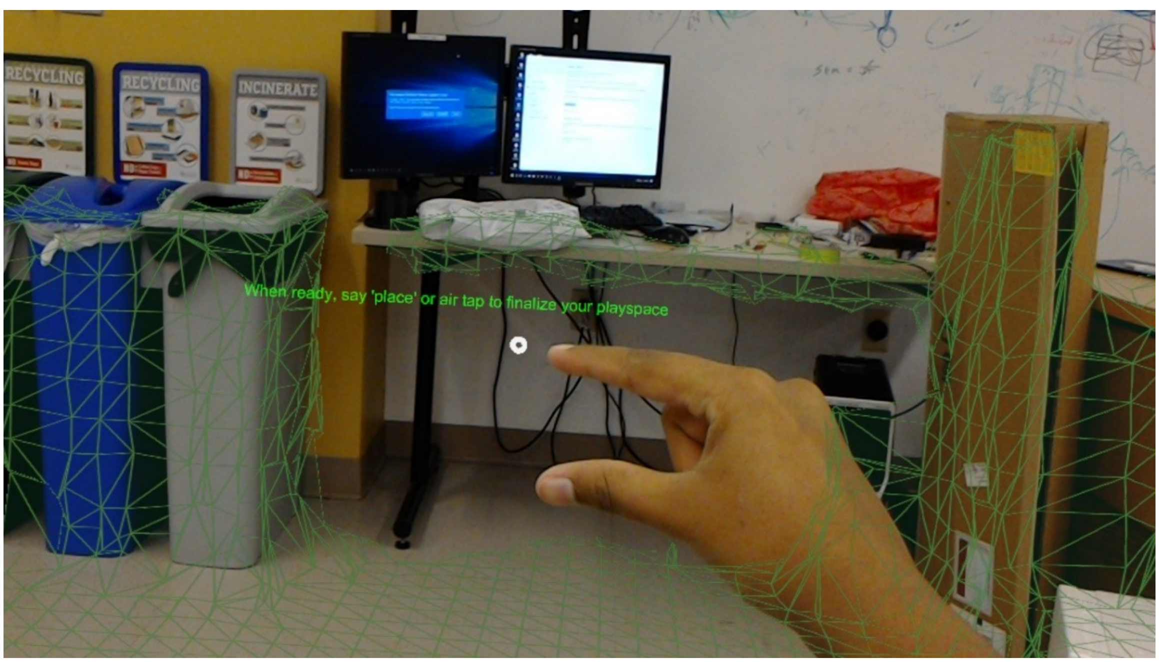


Figure 22. Second step in virtual PHAM frame placement.

Once the user clicks with an air-tap or says “place”, the application begins to look for optimal locations where the frame can be placed. Four such locations are highlighted by the placement of blue squares at each location. The user is prompted to look at one of the blue squares, as shown in Figure 23.

The user can select one of the four locations for frame placement by selecting one of the blue squares. This is done by looking at the square to be targeted and clicking with an air-tap or saying “select”, as shown in Figure 24. When the location is selected, all blue squares disappear and the frame is placed and ready to be used for training, as shown in Figure 25.

Figure 23. Third step in virtual PHAM frame placement.

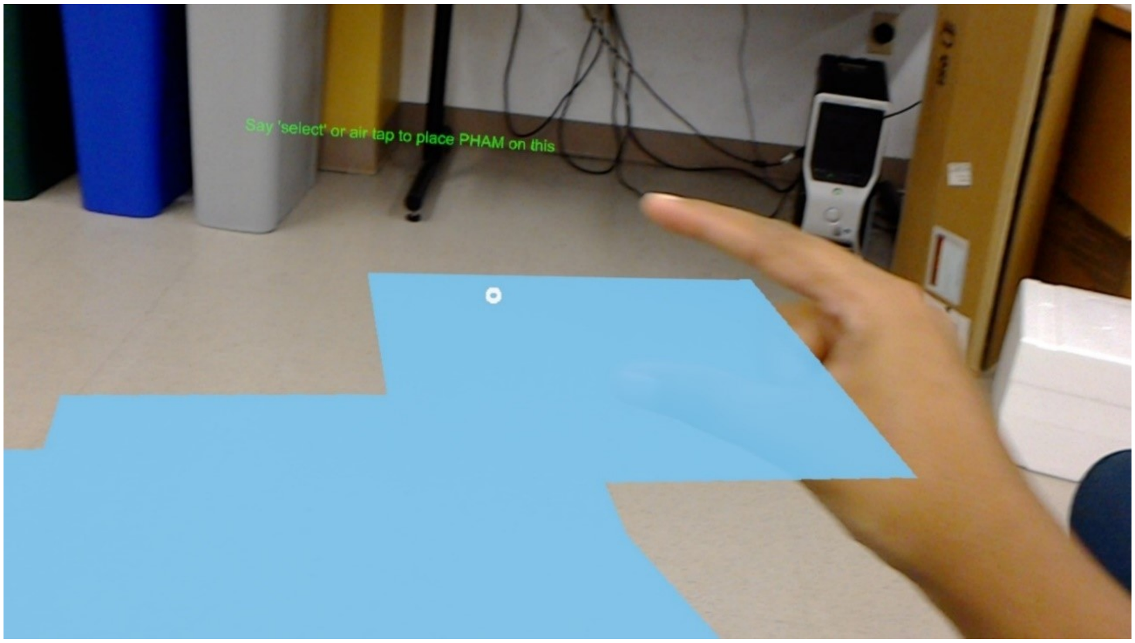


Figure 24. Fourth step in virtual PHAM frame placement.

Figure 25. Virtual PHAM ready to use in real-world environment.

3.3.2.2. Training exercises

Once the virtual PHAM frame is placed, the first case for the first trial is prompted, as shown in Figure 25. When the user is ready to begin the task, he/she must press the red button. This starts the timer and the button disappears, as shown in Figure 26.

The user must attempt to move the object to the target location and orientation within the timeout period set in the menu. If the user drops the object, a 'miss' is logged and the object is automatically placed at the position it was at during the start of the case and the user must attempt to move it again. If the user places the object in the target or the timer runs past the timeout period set, the timer is stopped and the duration of the case is logged. The task is marked as complete if the object was moved to the prompted target successfully or incomplete in case of a timeout. The object and the target appear for the next case followed by the red button, indicating that the timer has been reset. The same sequence of events occurs repeatedly, for each case, until the end of the training session.

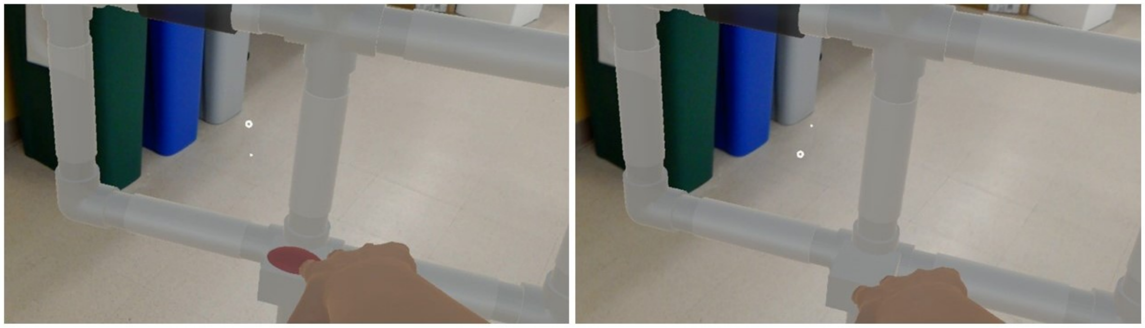


Figure 26. Screenshots of HoloPHAM showing the button activated timer: Button appears as red when new case is prompted (left), and disappears when touched with the virtual arm (right) starting the timer for the case.

3.4. Scoring system

The goal behind development of HoloPHAM was to create a virtual alternative for real-world PHAM. Keeping this goal in mind, the same scoring system was chosen for HoloPHAM as that used for real-world PHAM. This enables a direct comparison of user performance using PHAM and HoloPHAM. The scoring system used is described below.

3.4.1. Performance metrics

The 2D translational displacement ($\vec{\lambda}$), that is recorded using the pressure mat in real-world PHAM, is recorded through tracked position of the HMD in x-z plane of the Unity coordinate system, as shown in Equation 10. The 3D joint angles are recorded by tracking the movement of the virtual arm to ensure that all data collected is in the Unity coordinate system. This data is used to calculate 3D deviation of each joint just as in case of real-world PHAM. In addition to motion tracking data, the number of cases completed and completion times are logged as performance metrics.

$$\vec{\lambda} = \begin{bmatrix} p_B^x \\ p_B^z \end{bmatrix} \tag{10}$$

where $\vec{\lambda}$ is 2D translational displacement estimated in HoloPHAM, and p_B is the position of the HoloLens tracked in Unity coordinate system.

3.4.2. Final score and interpretation

The final score for performance (P_H) using HoloPHAM, as shown in Equation 11, is calculated similar to the method used for real-world PHAM. The scaling vector, k, is eliminated in this case as limit of tracking translational displacement is not limited to the dimensions of the pressure mat. Similar to PHAM performance score (P), the lower score (P_H) reflects a higher range of motion and better efficiency of task performance. Therefore, lower the score, better the performance of the user.

$$P_H = \frac{\|\vec{\lambda}\|_1 + \|\vec{\delta_B}\|_1 + \|\vec{\delta_S}\|_1}{\eta} \tag{11}$$

where P_H is the performance score for HoloPHAM, $\vec{\lambda}$ is 2D translation displacement, $\overrightarrow{\delta_B}$ is 3D deviation of the back, $\overrightarrow{\delta_S}$ is 3D deviation of the shoulder, and η is the completion rate.

This score can be used to draw comparisons between HoloPHAM and PHAM, which can be used to conduct comparative studies to evaluate HoloPHAM as a viable alternative to real-world PHAM.

4. Evaluation of BOTS

HoloPHAM was built as a virtual training protocol that would mimic training with PHAM. Virtual training protocols are heavily dependent on a good motion tracking system to drive movement of a virtual arm or prosthesis. As described in Chapter 3, a custom motion tracking system, BOTS, was designed and developed for HoloPHAM. Before applying BOTS to HoloPHAM, it was necessary to evaluate its performance in upper limb motion capture. This was achieved through a comparative study with a commercially available motion tracking system. This chapter describes this method used to evaluate BOTS and results of the study.

4.1. Approach

Microsoft Kinect was chosen as the standard motion tracking system for comparison with BOTS. The study was set-up by asking an able-bodied subject to wear the MTUs of BOTS as described in Chapter 3 and stand in front of the Kinect sensor. The subject was asked to attain a series of postures through an on-screen avatar that assumed each pose, as shown in Figure 27. Since subject chose to wear the MTUs of BOTS on the right arm, the poses selected as prompts involved movement of this arm. The prompt queue consisted of four different poses that were displayed for four seconds each. Subject was instructed to attain and hold the prompted pose within this four second window. Orientation data from both BOTS and Kinect were recorded simultaneously through the duration of the on-screen prompts.

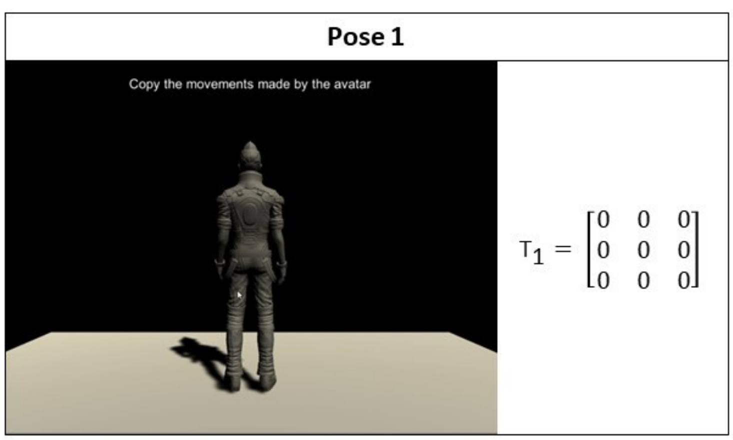
Three MTUs of BOTS were affixed to segments of subject's right arm along with a fourth reference MTU and orientation data was recorded in the form of calibrated quaternions representing the orientations of back, shoulder and elbow, as described in Chapter 3. Orientation data from the Kinect sensor was collected in the form of quaternions from the four joints tracked by the sensor - 'Shoulder-Spine', 'Shoulder-Right', 'Elbow-Right' and 'Wrist-Right' – which were then used to determine orientations of the back, shoulder and elbow for comparison with data from BOTS.

Data obtained from pose 1, as shown in Figure 27, was used as a calibration step to transform the coordinate systems of the Kinect sensor and BOTS to the Unity coordinate system. The quaternions from subsequent poses were then transformed to Unity coordinate system based on the outcome of the calibration step. These calibrated quaternions were then represented as Euler angles for easier interpretation of results. The processed orientation data that was analyzed represented the relative orientations of the back, shoulder and elbow. The relative orientations of these joints in the avatar were used as target orientations for each pose, as shown in Equation 12 and Figure 27.

$$T_P = \begin{bmatrix} \overrightarrow{T_B} \\ \overrightarrow{T_S} \\ \overrightarrow{T_E} \end{bmatrix} = \begin{bmatrix} \theta_B & \varphi_B & \psi_B \\ \theta_S & \varphi_S & \psi_S \\ \theta_E & \varphi_E & \psi_E \end{bmatrix} \tag{12}$$

where T_p represents the target orientation for each pose (p), (θ, φ, ψ) represent roll, pitch and yaw respectively, and B, S, E represent the joints – back, shoulder and elbow respectively.

Joint orientations from the 'hold' period of each pose was compared with the target joint orientations for that pose. This was used to determine the root mean square error (RMSE) of estimated joint angles from target joint angles. RMSE and mean joint angles ($\vec{\mu}$) from both BOTS and Kinect were computed for each pose, as shown in Equation 13a & b.



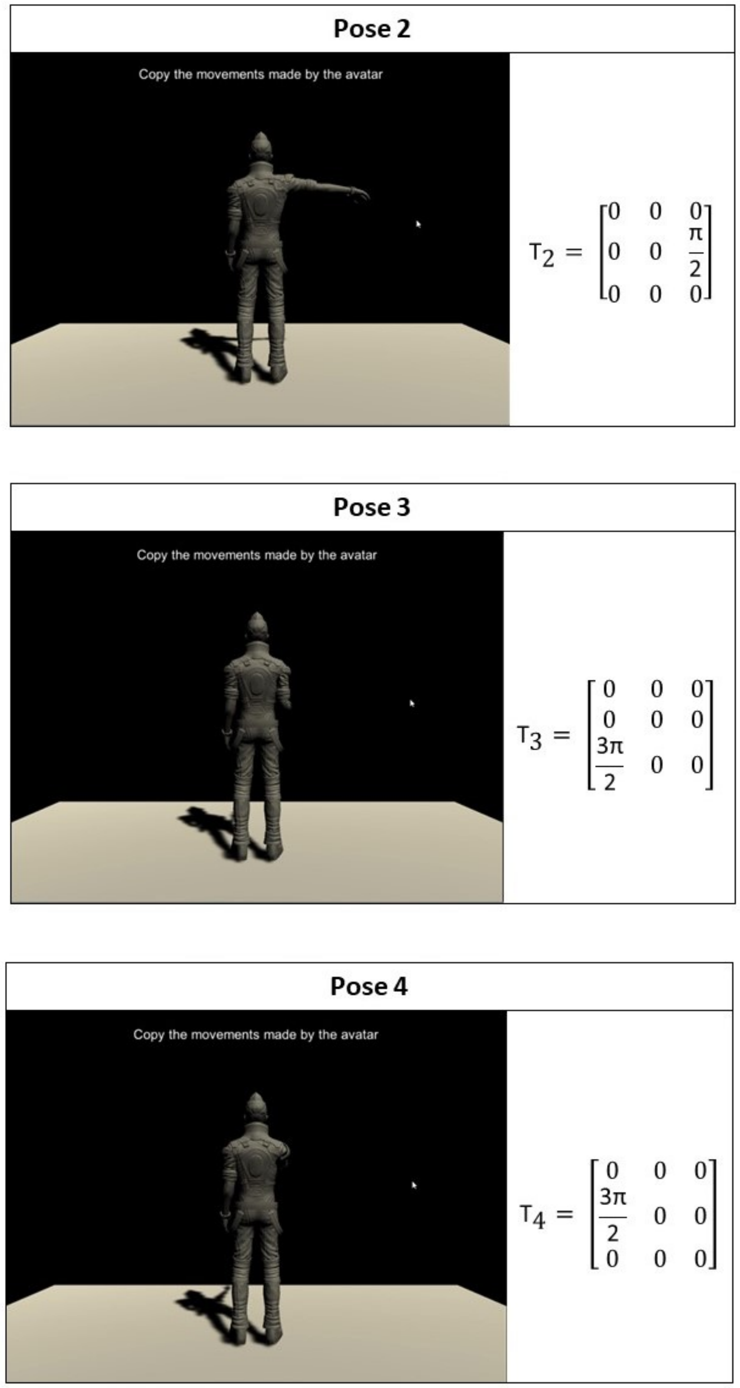


Figure 27. Poses that subject attains and holds through the duration of the study along with target orientation of joints for each pose.

$$RMSE_J^p = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\begin{bmatrix}\theta_J \\ \varphi_J \\ \psi_J\end{bmatrix}_p^n - \vec{T}_p^n\right)^2} \tag{13a}$$

$$\vec{\mu}_J^p = \frac{1}{N}\sum_{n=1}^{N}\begin{bmatrix}\theta_J \\ \varphi_J \\ \psi_J\end{bmatrix}_p^n \tag{13b}$$

where $RMSE_J^p$ and $\vec{\mu}_J^p$ represent root mean square error of and mean joint angle respectively over samples of the 'hold' phase of each pose (p), J represents the joint, N represents number of samples in the 'hold' phase of each pose and p represents the pose number.

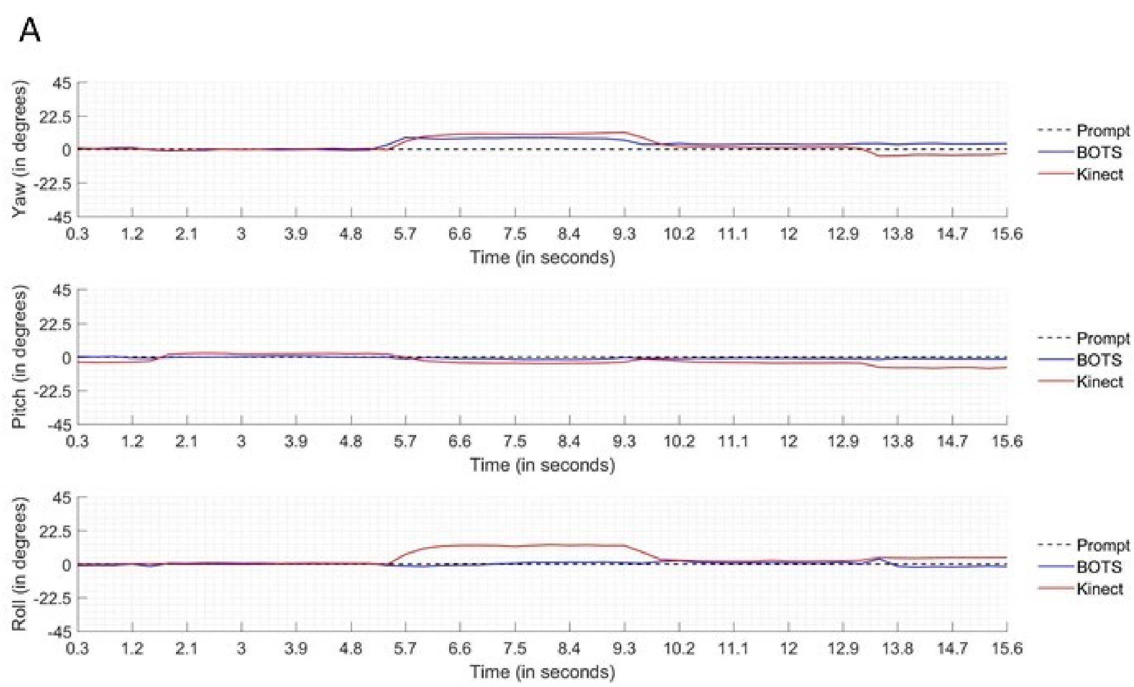
The RMSE values of estimated joint angles from the target orientations were also computed over samples from the 'hold' phase of all poses, as shown in Equation 14, to reflect the overall performance of both motion tracking systems.

$$RMSE_J = \sqrt{\frac{1}{P}\sum_{p=1}^{P}\frac{1}{N}\left(\begin{bmatrix}\theta_J \\ \varphi_J \\ \psi_J\end{bmatrix}_p^n - \vec{T}_p^n\right)^2} \tag{14}$$

where $RMSE_J$ is the RMSE of joint angles over samples of 'hold' phase of all poses, P is the number of poses, and J is the joint.

4.2. Results

First, the joint angles computed using both BOTS and Kinect were visualized with along with the target joints angles prompted during each time period of the study, as shown in Figure 28. At first glance, BOTS appear to have performed better than Kinect in tracking orientation of each joint, particularly the elbow. However, further statistical analysis of data was done to verify this observation.



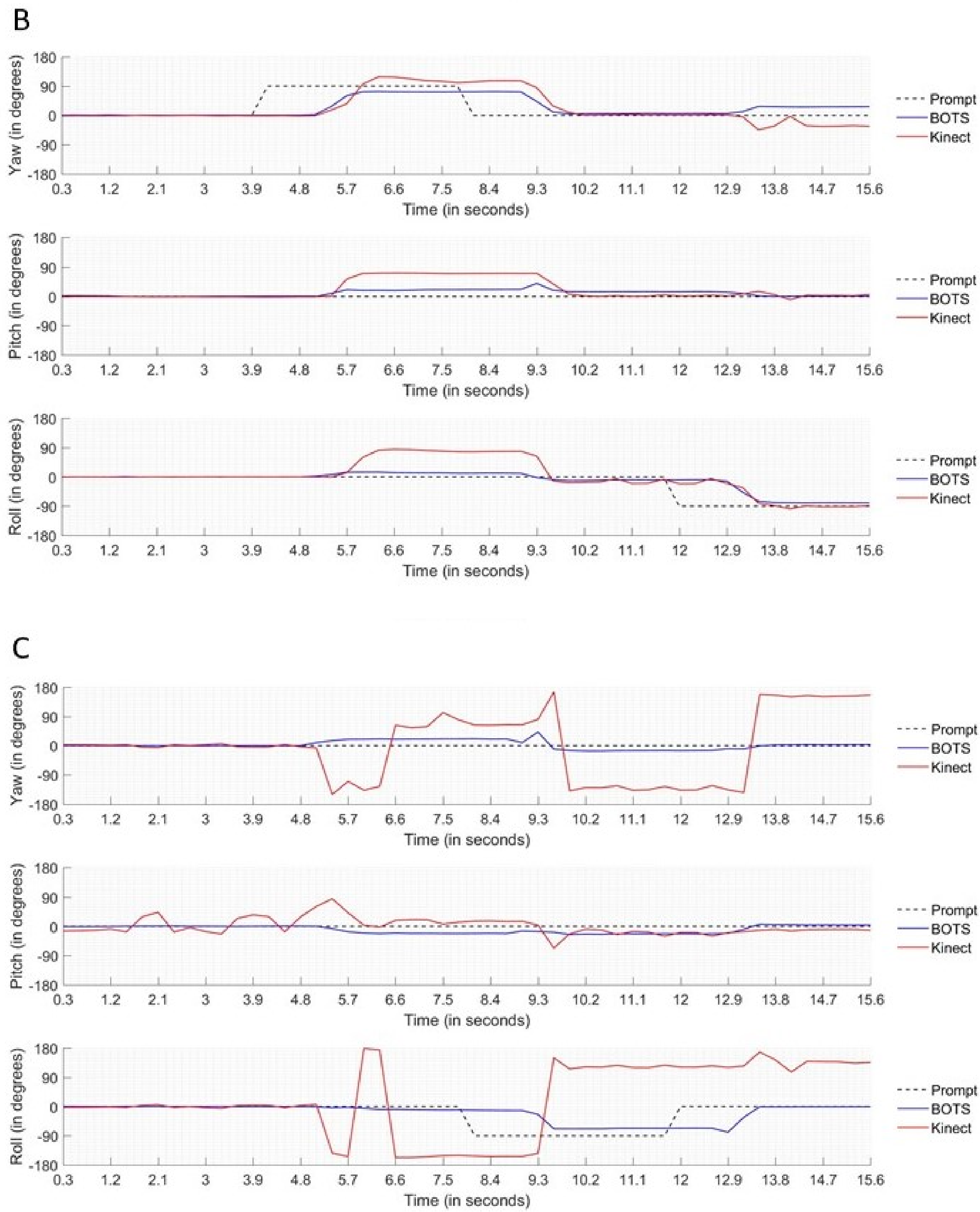


Figure 28. Euler angles of each joint obtained from BOTS (blue) and Kinect (red) along with the target orientations prompted (black, dotted) at

each time point: A. Represents Euler angles of the back, B. Represents Euler angles of the shoulder, and C. Represents Euler angles of the elbow.

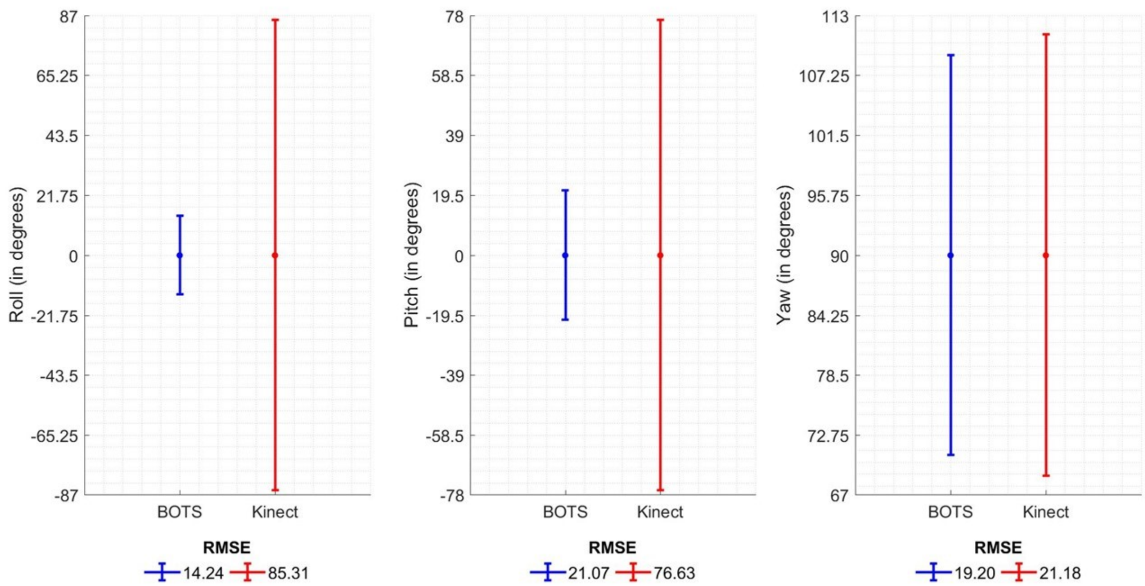
As data from both motion tracking systems were simultaneously obtained from the same subject, a correlation analysis could provide valuable information on the differences between the two systems. If motion tracking performance of the two systems were very similar, then the resulting correlation factor would be closer to +1. Based on observations made from the plot, both systems did not show similar performance in motion tracking. Correlation coefficient for joint angles from BOTS and Kinect support this observation. As shown in Table 3, Euler angles of the back and elbow tracked by BOTS and Kinect are weakly correlated. The orientations of shoulder joint obtained from both systems were more similar, but still only moderately correlated. This shows that there is a significant difference in performance of both systems and leads to the question – Which system performed better?

	Back	**Shoulder**	**Elbow**
Roll	-0.11	0.84	-0.40
Pitch	0.17	0.81	0.17
Yaw	0.67	0.83	0.41
Overall	**0.32**	**0.80**	**-0.15**

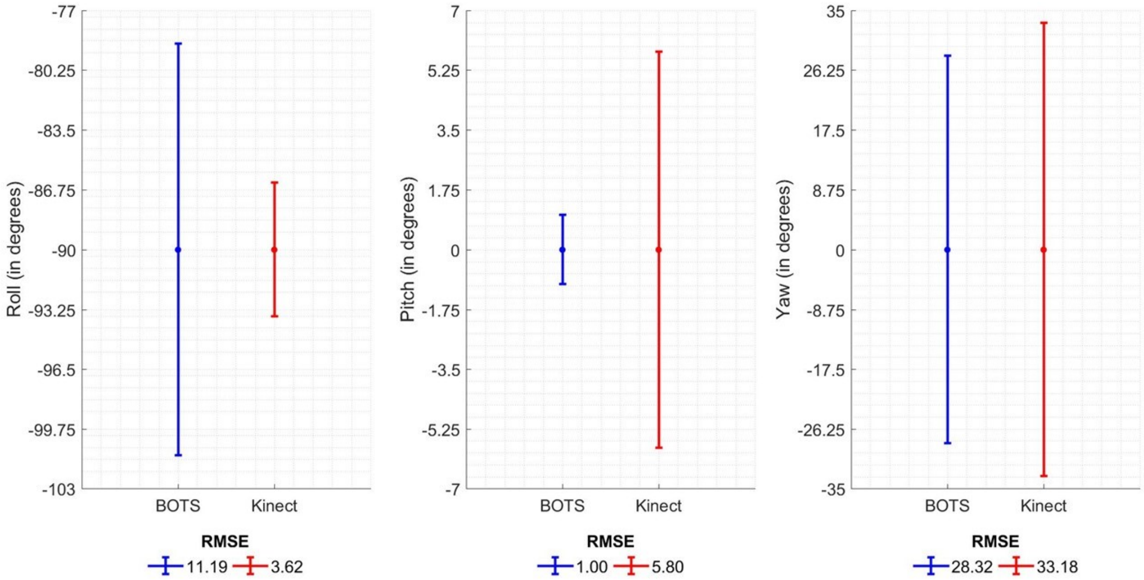
Table 3. Correlation coefficients resulting from correlation analysis on Euler angle representation of each joint from both BOTS and Kinect.

In order to answer this question, $RMSE_J^p$ of joint angles from BOTS and Kinect were determined for each pose (**Appendix**). The $RMSE_J^p$ of shoulder and elbow angles for two of the poses are shown in Figure 29. The $RMSE_J$ of joint angles from both BOTS and Kinect across all poses were also determined, as shown in Table 4.

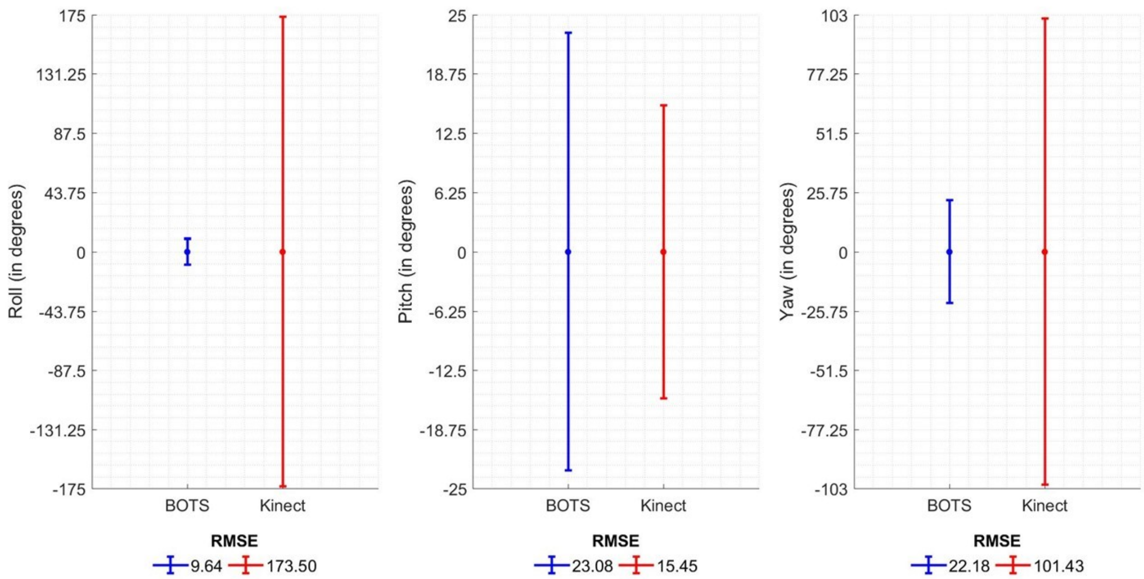
A



B


Roll (in degrees)
-77
-80.25
-83.5
-86.75
-90
-93.25
-96.5
-99.75
-103
BOTS
Kinect
RMSE
11.19
3.62
Pitch (in degrees)
7
5.25
3.5
1.75
0
-1.75
-3.5
-5.25
-7
BOTS
Kinect
RMSE
1.00
5.80
Yaw (in degrees)
35
26.25
17.5
8.75
0
-8.75
-17.5
-26.25
-35
BOTS
Kinect
RMSE
28.32
33.18

C


Roll (in degrees)
175
131.25
87.5
43.75
0
-43.75
-87.5
-131.25
-175
BOTS
Kinect
RMSE
9.64
173.50
Pitch (in degrees)
25
18.75
12.5
6.25
0
-6.25
-12.5
-18.75
-25
BOTS
Kinect
RMSE
23.08
15.45
Yaw (in degrees)
103
77.25
51.5
25.75
0
-25.75
-51.5
-77.25
-103
BOTS
Kinect
RMSE
22.18
101.43

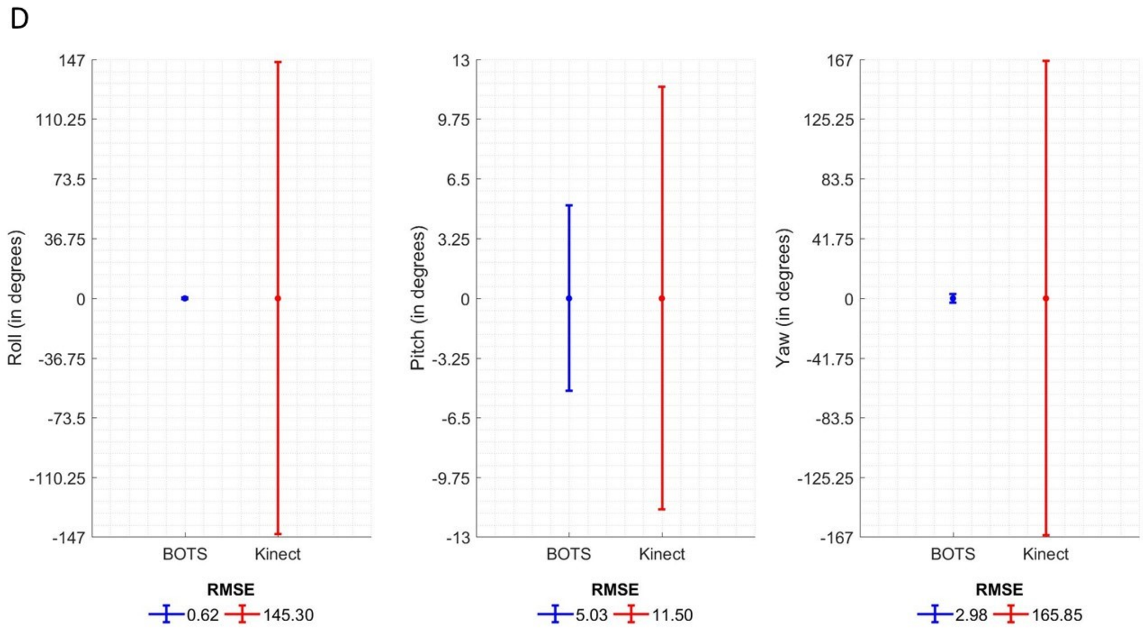


Figure 29. $RMSE_J^p$ of joint angles from each motion tracking system presented as range of error around the target joint angles of pose (p) for two poses. A and C show the shoulder orientations for poses 2 and 4 respectively, B and D show the elbow orientations for poses 2 and 4 respectively.

	Back		**Shoulder**		**Elbow**	
	BOTS	**Kinect**	**BOTS**	**Kinect**	**BOTS**	**Kinect**
Roll	1.23	6.62	9.93	41.05	12.42	130.58
Pitch	0.99	4.64	12.32	36.27	16.30	19.14
Yaw	4.50	5.42	16.38	18.67	13.15	113.56

Table 4. $RMSE_J$ values, where J represents each joint, summarizing deviation of joint angles tracked by each system from the target joint angles prompted.

Consistently higher $RMSE_J^P$ values across all poses show that the Kinect sensor tracks joint orientations with lower accuracy than BOTS. This is supported by a two-sample *z*-test performed on $RMSE_J$ values shown in Table 4, which showed that there is a statistically significant difference ($p < 0.05$) between the $RMSE_J$ values of joint angles from BOTS and Kinect across all four poses, with higher $RMSE_J$ values in the case of Kinect. A particularly high error range was observed in case of elbow joint tracking by the Kinect sensor. This coincides with reports from previous studies using the Kinect sensors, where inaccurate interpolation of wrist joint positions and orientations was reported when it was not clearly detected by the sensor's camera. [25]

4.3. Conclusion

BOTS showed improved performance in tracking of upper limb movement than the Kinect. $RMSE_J$ values of joint angles from BOTS still indicated a large deviation from the target joint angles for each pose which could be a reflection of human error. For example, while the subject was prompted to attain pose 2, he/she might have attained the position with a slight rotation around the x-axis or y-axis of the shoulder joint or attained a pose in which the upper arm is not exactly perpendicular to back. These error values could be reduced by adjusting the target joint angles to account for such human errors. Overall, BOTS tracks upper limb movement with a level of accuracy suitable for application in virtual training environments with the added benefit of unconstrained mobility.

5. Future Directions

HoloPHAM is the first immersive AR environment designed for myoelectric prosthesis user training. This training environment can serve as a medium to explore the potential applications of immersive AR in myoelectric training for prosthesis users. This chapter describes some of these potential applications of HoloPHAM and research questions that the system can help answer.

5.1. Future work with HoloPHAM

The work described here mainly covers the development of HoloPHAM. Its effectiveness on amputee training and performance with a myoelectric prosthesis is yet to be determined. This section describes different experiments to evaluate the effectiveness of HoloPHAM and explore the contribution of immersive AR to the observed changes in prosthesis user performance.

5.1.1. Amputee training with HoloPHAM

Sometimes training systems are developed with the intent to improve prosthesis user's performance. Preliminary evaluations during development of such training systems is performed on able-bodied subjects. While such studies serve the purpose of system evaluation, they do not reflect the effect that the training protocol might have on prosthesis users. Therefore, the effectiveness of a new training system can be best determined by studies performed on amputees with the new system.

Keeping this in mind, the first step to evaluating HoloPHAM as a viable training system is to study the effects of daily training sessions with HoloPHAM on amputee performance with a prosthesis over multiple days. As this system was intended as an alternative to PHAM, comparing these results with the effects of training sessions using PHAM on amputee performance with a prosthesis. Based on previous studies on VR training systems [24], [34], I hypothesize that HoloPHAM will influence amputee performance with the prosthesis in a manner similar to the effects of PHAM on prosthesis user performance. Training with HoloPHAM over multiple days should show an improvement in amputee performance with a prosthesis that can be determined using the performance scores from each training session.

5.1.2. Effectiveness of AR in user training

As described in Chapter 2, three factors – increased excitement, physical fidelity, and cognitive fidelity - have been identified as possible causes for increased user participation in training and performance with the prosthesis. [16] While increased physical fidelity has been confirmed as a causal factor through previous studies which show that training tasks designed to mimic ADLs prove more effective in improving user functionality with a prosthesis than just control training [21], fewer studies have explored the effect of increased excitement or increased cognitive fidelity on prosthesis user training. HoloPHAM incorporates two of the three factors stated and thus form a good choice as one of the VR training systems than can be used to determine the level at which these factors affect prosthesis user training.

The comparative evaluation of HoloPHAM with PHAM described in the previous section can also shed some light on the effect of increased excitement on user performance. As HoloPHAM has been designed to mimic PHAM, any differences in user performances on the two training systems could be a result of increase excitement from the experience of immersive AR. Therefore, higher improvement in prosthesis user performance after training in HoloPHAM can serve as evidence supporting increased excitement or motivation as a causal factor for improved user participation in training and subsequent performance with the prosthesis.

Increasing the cognitive load during training through distracting environmental factors such as loud sounds can simulate conditions that are more likely to be faced in daily life. Such external factors can be incorporated during training with HoloPHAM to provide information on the effect of increased cognitive fidelity on the effectiveness of the training system. Comparison of user performance scores after training in such conditions with those obtained after training in the absence of such distracting conditions can verify increased cognitive fidelity as a causal factor for improved user performance after training.

5.2. Future of AR in user training

The design of HoloPHAM as a portable immersive AR training system for prosthesis users introduces a new set of potential applications such as take-home training systems and the development of virtual training environments from real-world objects present in a work space using object recognition algorithms. This section explores these two potential applications in greater detail.

5.2.1. Take-home training systems

Most training protocols utilized in functional use training of the prosthesis phase of occupation therapy involve long sessions and, often, commutes to a rehabilitation center. This is considered tedious and, sometimes, leads to lapses in delivery of the full-length of planned training sessions. Portable AR training systems such as HoloPHAM can be sent with an amputee as a take-home training system to learn prosthetic control. The ability to train at the comfort of one's home might serve as a motivational factor to continue training regularly, which can result in better functionality using a prosthesis. Advancements in technology also allow for remote access of performance metrics logged after every training session, enabling easy monitoring of progress and effectiveness of the current training plan. This allows for possible adjustments and optimization of the training plan to specifically suit each user, thus maximizing possible improvement in user performance from training.

5.2.2. Application of object recognition in training

Immersive AR displays such as the Microsoft HoloLens are equipped with a camera to enable spatial perception and understand of the real-world environment. This feature enables the positioning of objects at specific locations such as on the floor as in the case of PHAM frame placement in HoloPHAM. However, the camera can be used for finer mapping of the surroundings to detect the shapes of objects present using object recognition algorithms. Such information from the environment can be used to overlay virtual objects that match the shape of the real-world objects that can be manipulated by a virtual arm, thus creating a reach-grasp-release task. The AR training system can be designed to display target locations upon recognition of an object prompting the user to move the object to the target location using a virtual arm driven by an HMI similar to that used in HoloPHAM. Figure 30 shows an example of the kind of training environment visualized for application of object recognition for prosthesis user training in AR. In this example, the sphere represents a virtual object displayed over a real-world object present on a table. Each table mat represents a possible target to which the virtual object can be moved. The RGR task is prompted with a specific target, as shown in the lower panel of Figure 30. All physics interactions in this virtual environment are enabled through the Leap Motion controller that tracks hand movements which are used to control the virtual arm. The virtual room depicted in Figure 30 is just a representation of the real-world environment. This would be replaced by the view of the real-world environment and virtual copies of real-world objects rendered through shape recognition to create an impromptu AR experience.

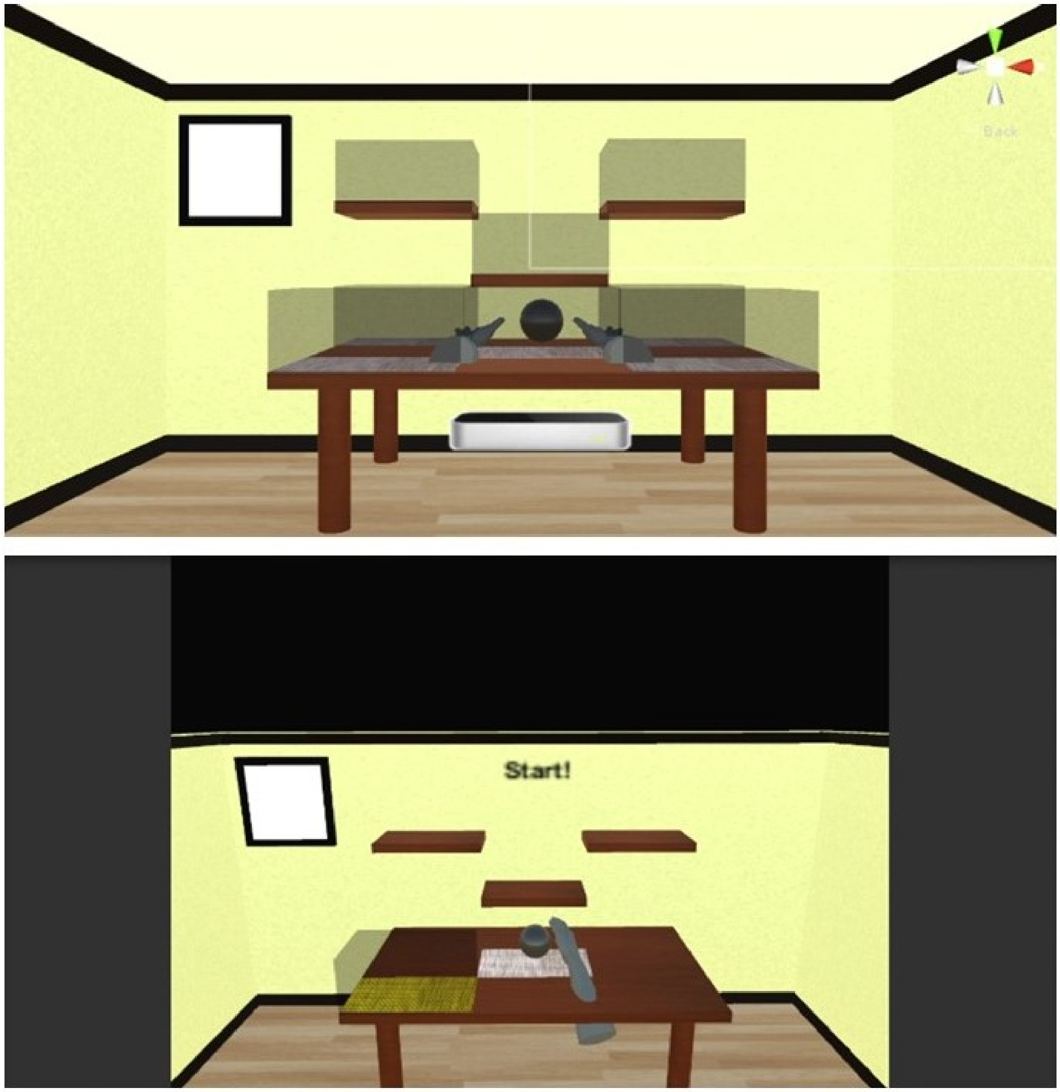


Figure 30. Visual representation of a training environment that can be designed for an object recognition-based AR system. The upper panel shows environment set-up, and the lower panel shows the object and RGR task prompted during the training session.

5.3. Concluding Remarks

HoloPHAM was designed to introduce immersive AR into the field of myoelectric prosthesis training. Current immersive AR technology is limited and expensive, thus making applications such as take-home training systems plans for a slightly more distant future. However, HoloPHAM can be utilized as a tool to explore the use of AR in task-based myoelectric control training and effectiveness of such systems in improving prosthesis user performance, which can provide valuable information moving forward with development of new technology for application in rehabilitation therapy.

Appendix

A.1. Tabular representation of RMSE of joint angles for each pose

A.1.1. BOTS

This table shows the $RMSE_J^p$ values (in degrees) for each pose, p, calculated from joint angles obtained using BOTS.

Pose	Back			Shoulder			Elbow		
	Roll	Pitch	Yaw	Roll	Pitch	Yaw	Roll	Pitch	Yaw
1	0.56	0.32	0.37	0.19	1.11	0.65	0.16	0.54	0.30
2	0.99	1.30	7.97	14.24	21.07	19.20	9.64	23.08	22.18
3	1.44	0.95	3.52	10.78	15.40	5.95	24.51	25.25	16.67
4	1.86	1.32	3.88	11.19	1.00	28.32	0.62	5.03	2.98

A.1.2. Microsoft Kinect

This table shows the $RMSE_J^p$ values (in degrees) for each pose, p, calculated from joint angles obtained using the Microsoft Kinect sensor.

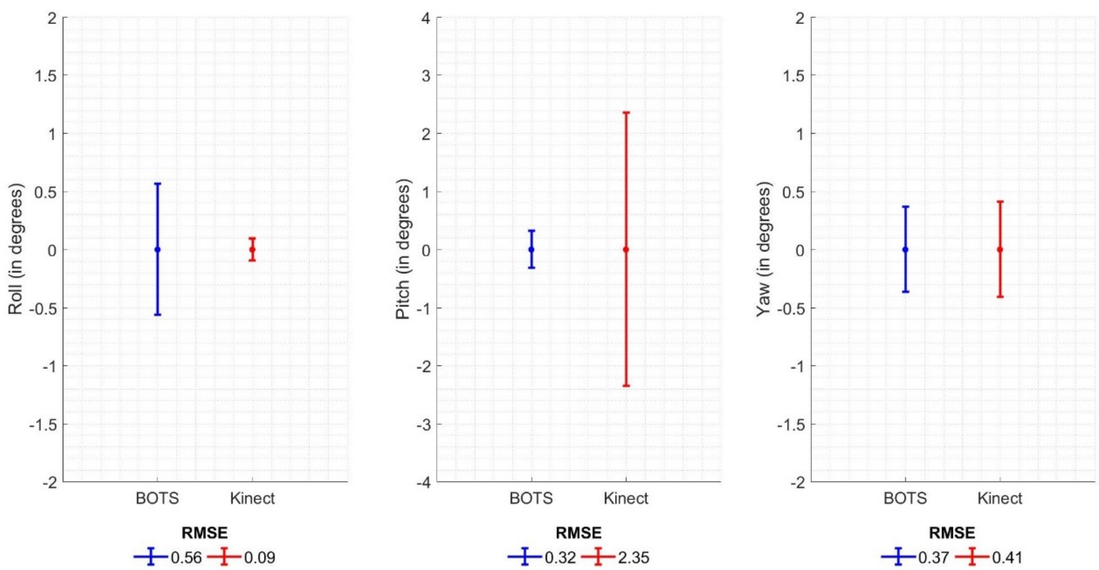
Pose	Back			Shoulder			Elbow		
	Roll	Pitch	Yaw	Roll	Pitch	Yaw	Roll	Pitch	Yaw
1	0.09	2.35	0.41	0.26	0.55	0.84	4.29	28.44	4.36
2	13.05	4.14	10.59	85.31	76.63	21.18	173.50	15.45	101.43
3	2.50	3.66	1.87	17.09	3.87	4.20	159.69	21.66	142.20
4	4.57	7.80	4.04	3.62	5.80	33.18	145.30	11.50	165.85

A.2. Graphical representation of RMSE of joint angles for each pose

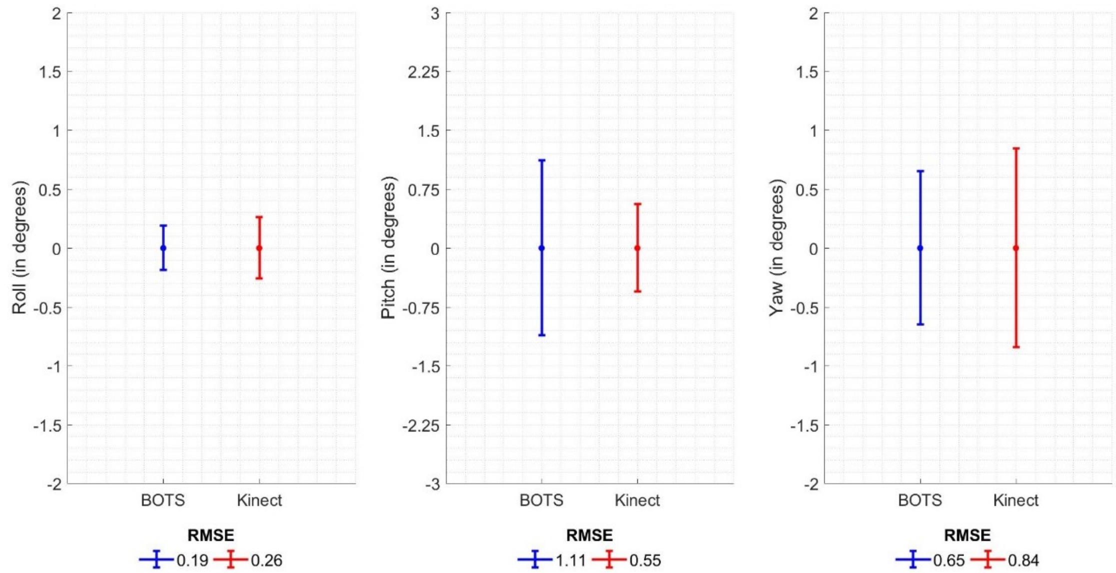
This section contains a graphical representation of the $RMSE_J^p$ values of the joint angles estimated using BOTS and the Kinect sensor for every pose.

A.2.1. Pose 1

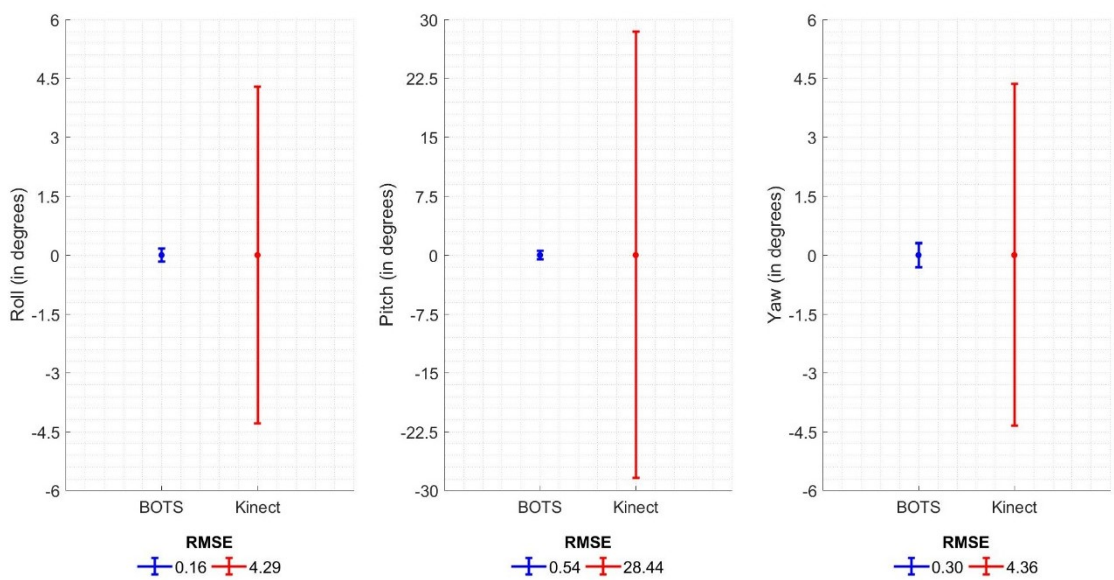
A.2.1.1. Back



A.2.1.2. Shoulder

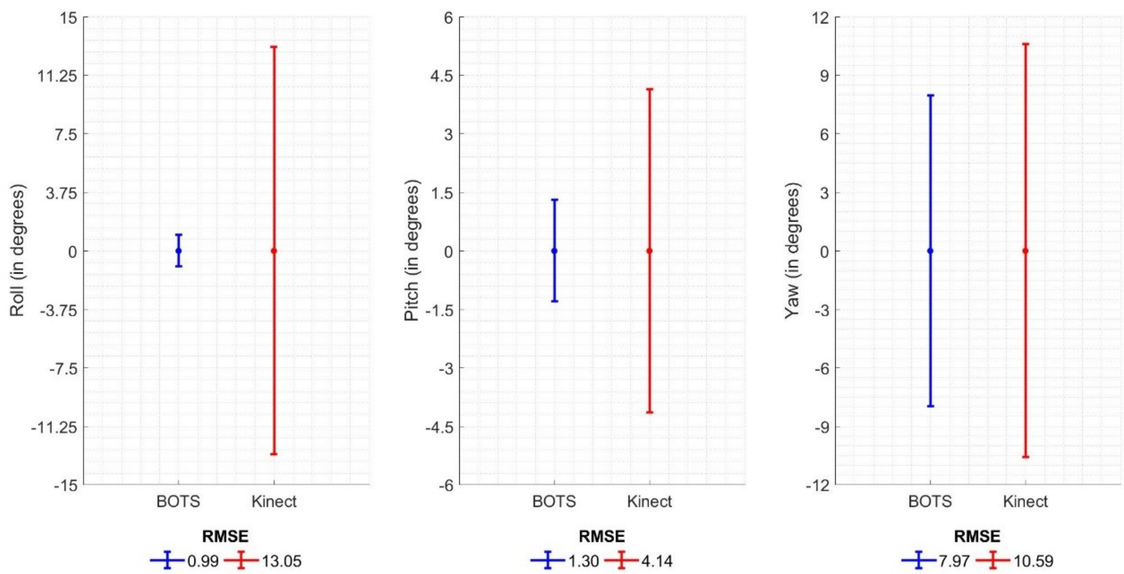


A.2.1.3. Elbow

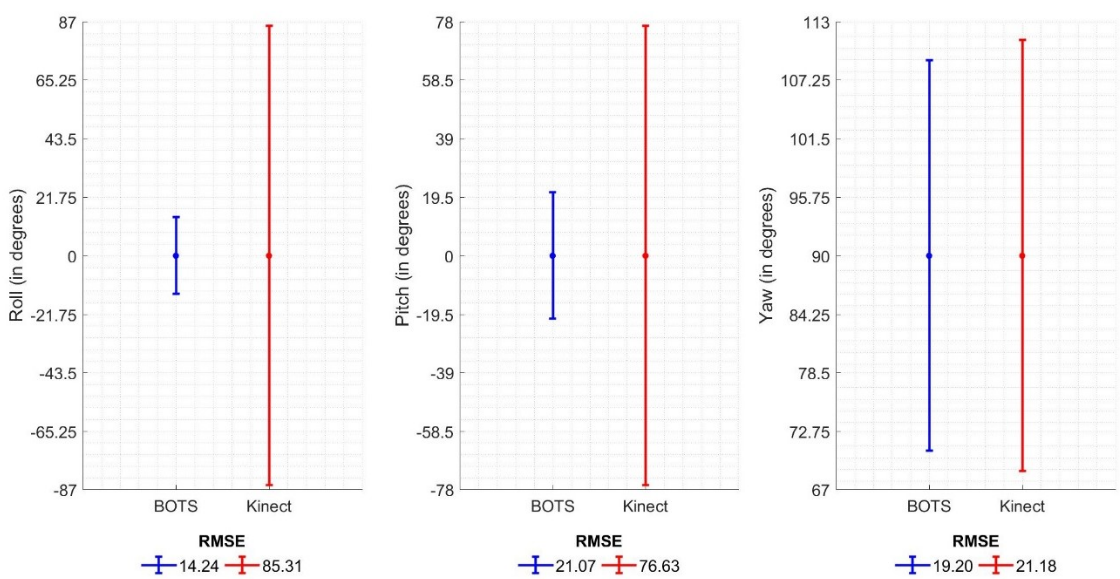


A.2.2. Pose 2

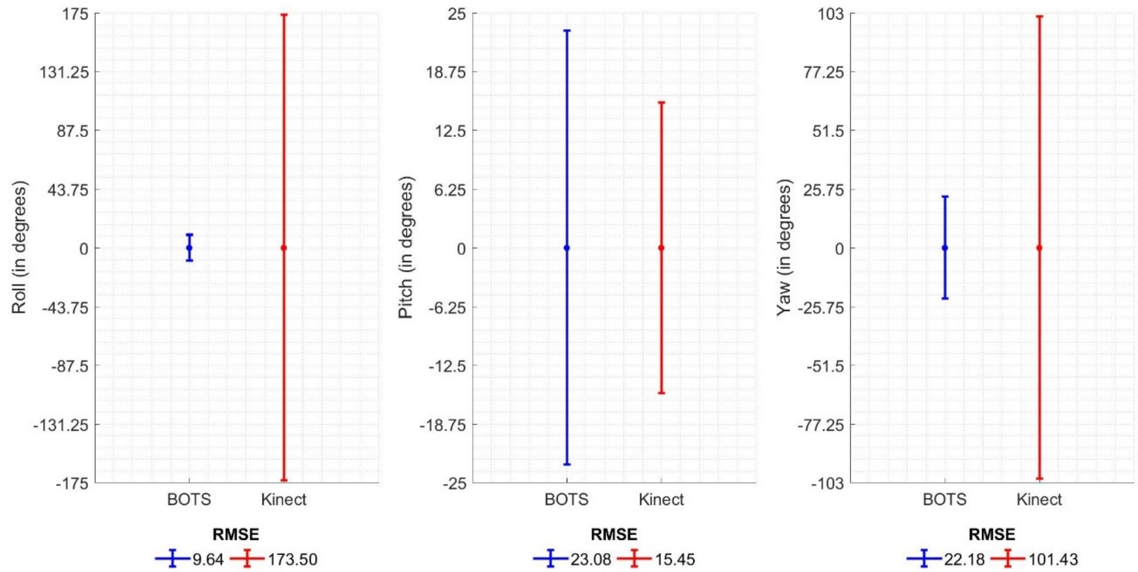
A.2.2.1. Back



A.2.2.2. Shoulder

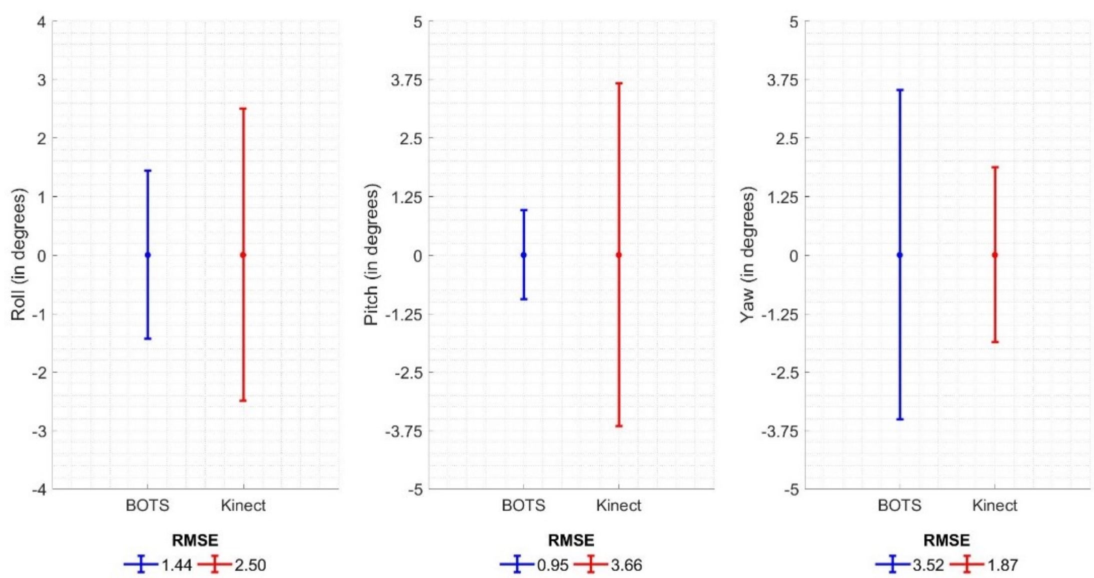


A.2.2.3. Elbow

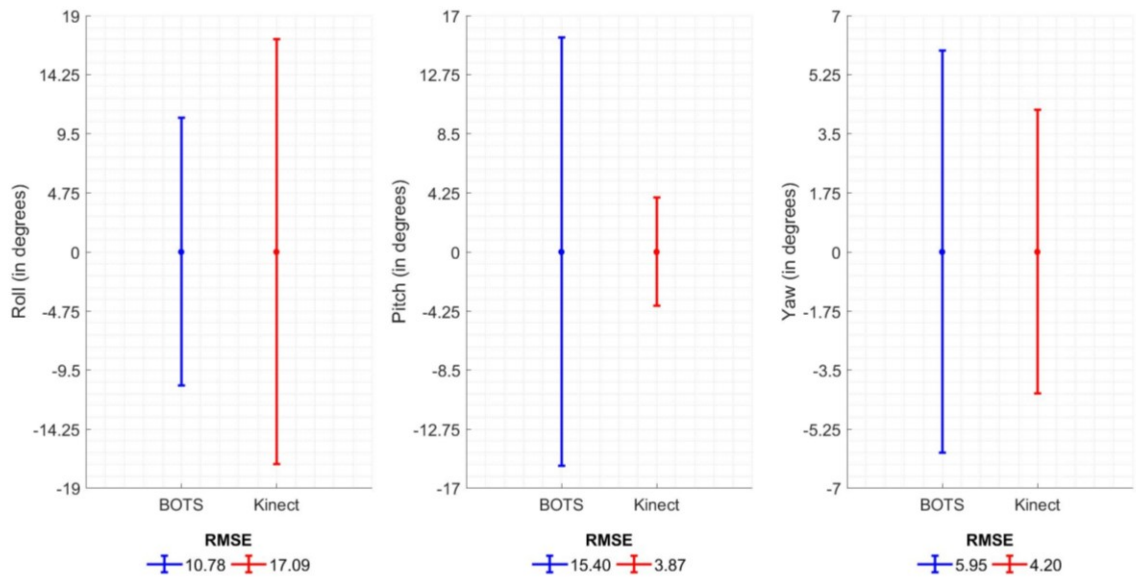


A.2.3. Pose 3

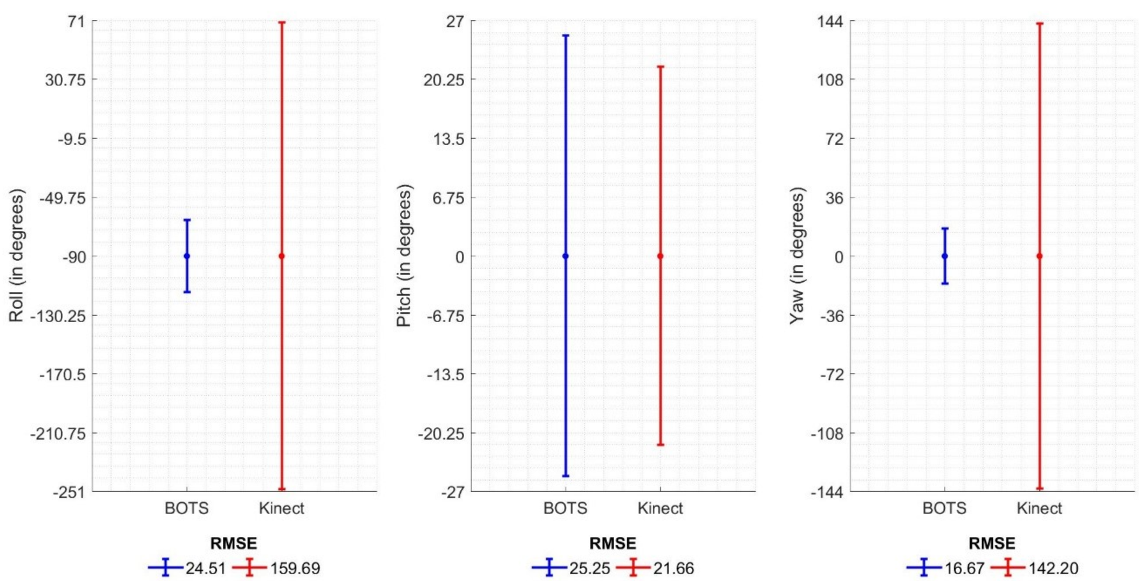
A.2.3.1. Back



A.2.3.2. Shoulder

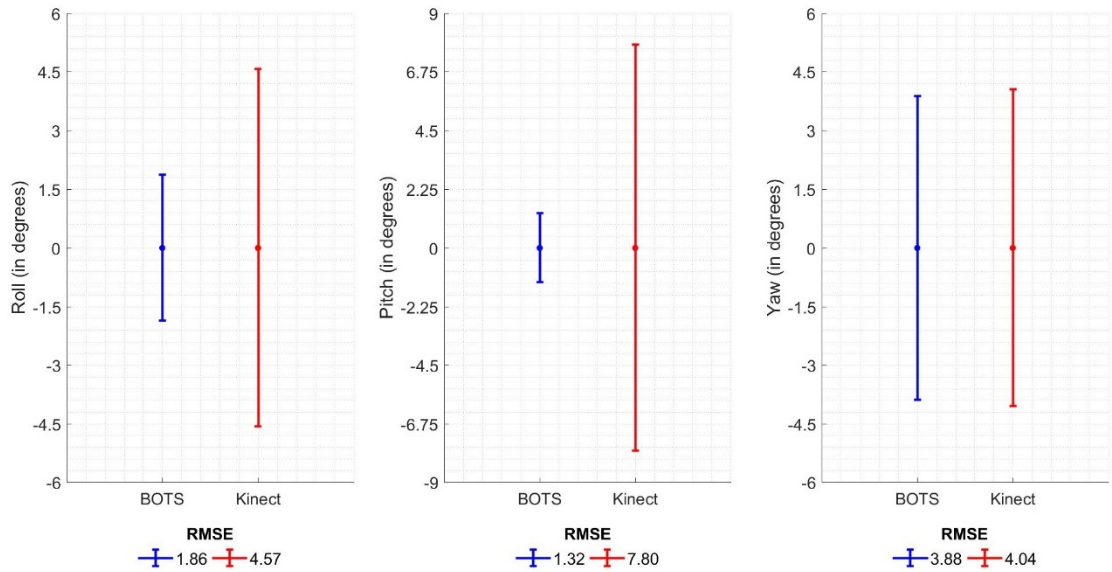


A.2.3.3. Elbow

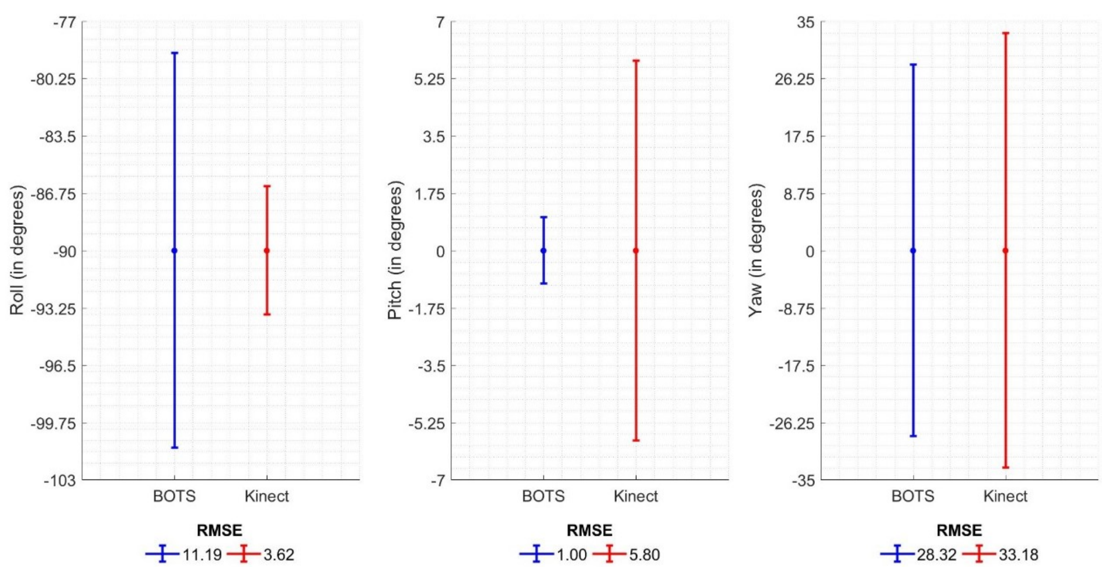


A.2.4. Pose 4

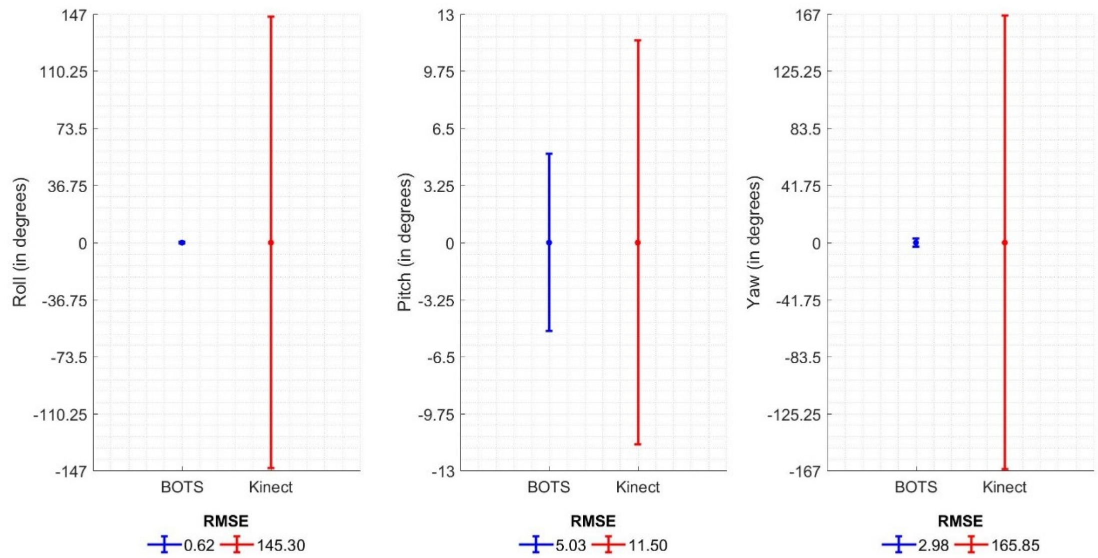
A.2.4.1. Back



A.2.4.2. Shoulder



A.2.4.3. Elbow


147
110.25
73.5
36.75
0
-36.75
-73.5
-110.25
-147
Roll (in degrees)
BOTS
Kinect
RMSE
0.62
145.30
13
9.75
6.5
3.25
0
-3.25
-6.5
-9.75
-13
Pitch (in degrees)
BOTS
Kinect
RMSE
5.03
11.50
167
125.25
83.5
41.75
0
-41.75
-83.5
-125.25
-167
Yaw (in degrees)
BOTS
Kinect
RMSE
2.98
165.85

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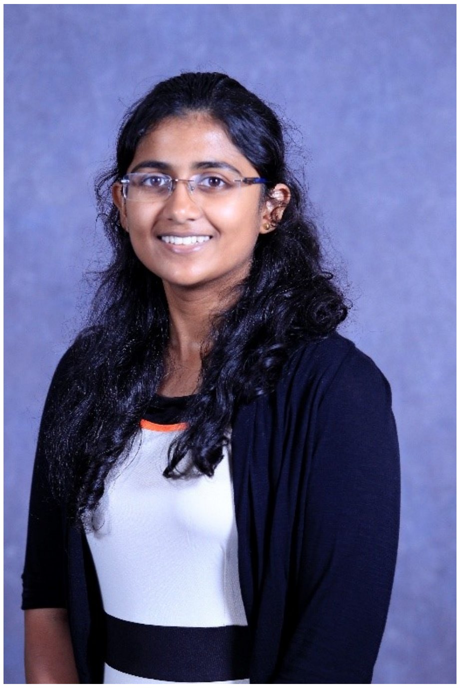
Curriculum Vitae



Juhi Baskar was born in Bellevue, WA on November 16, 1993 to Baskar Kothandaraman and Apitha Iyer. She began pursuing her Bachelors of Technology in Bioengineering in 2011 at SASTRA University in Thanjavur, India. She graduated from SASTRA University in 2015, after completing an internship at University of Wisconsin – Madison and a semester at Weill Cornell Medical College, NY. She moved on to pursue her Masters of Science in Engineering from Johns Hopkins University in 2015, majoring in Biomedical Engineering. She has spent the last two years as a graduate research assistant at the Neuroengineering and Biomedical Instrumentation Lab at Johns Hopkins University working on projects from different research areas in the field. Her current research focuses on the application of immersive augmented reality in myoelectric prosthesis user training.